Transmission Integration and the Market for Congestion Revenue Rights: The Case of the Texas Electricity Market

Gaurav Doshi* Xiaodong Du**

Abstract

Texas electricity market saw a recent integration of electricity transmission as a part of Competitive Renewable Energy Zones (CREZ). Exploiting the commissioning date of CREZ based transmission integration as an exogenous shock, we analyze the effect of transmission expansion on market clearing prices of Congestion Revenue Rights (CRR). Reduced form estimates suggest that excess transmission led to a lowering of CRR prices for contracts at all Times of Use. We find strong evidence of spatial, distributional, and firm specific heterogeneity. The paper shows that transmission expansion enhanced efficiency of the CRR market in terms of a spatial convergence in prices and a decrease in aggregate auction expenditure of approximately $260 million over a period of 4.5 years post CREZ.

Keywords: Congestion Revenue Rights, CREZ, market integration, transmission expansion

JEL Codes: L51, L94, Q41

. *University of Wisconsin-Madison, Department of Agricultural and Applied Economics. gdoshi2@wisc.edu.

. **University of Wisconsin-Madison, Department of Agricultural and Applied Economics and Renk Agribusiness Institute. xdu23@wisc.edu.

1 Introduction

Texas electricity market is marked by a substantial wind energy penetration that accounted for about 17 percent of energy use in 2017[1], up from 9 percent in 2011, whereas wind generation capacity in 2017 was 22 percent (ERCOT 2018a). This is in part credited to the recent expansion of electricity transmission built as a part of Competitive Renewable Energy Zones (CREZ) that seek to harness the wind energy in predominantly western part of Texas and add to the existing electricity transmission, thereby relieving the growing demand for electricity across the state. CREZ was an ambitious project both in terms of scale and cost – 3,600 miles of open access transmission lines with the cost of about $6.8 billion (Lasher 2014)[2]. The project completed in January 2014, offers a unique setup to study the impact of transmission expansion on the Texas electricity market and explore the underlying heterogeneity.

In this paper, we focus on the market of Congestion Revenue Rights (CRR) that play a vital role in the Texas wholesale electricity market. CRRs are financial contracts that enable the holders (e.g., generating companies and retailers) to hedge the risk due to transmission congestion costs in the Day Ahead Market (DAM). CRRs also serve as a financial instrument used for speculative purposes by various market players such as financial traders. Our paper answers the question about how the addition of electricity transmission lines affects the prices of CRR? We also measure how this effect varies across different times of the day and spatial locations? Further, we discern various aspects of heterogeneity and provide justification for them.

We study the impact of transmission integration[3] as a part of CREZ on the monthly price of CRRs over December 2010 – May 2018. We use final commissioning date of all CREZ related transmission infrastructure to be in-service as an exogenous change to the system. The construction of this transmission network

1. The Peak share of wind was 54 percent in October 27, 2017 at 4 AM.
2. Open-access means that the use is not limited to wind energy.
3. We use the terms transmission 'integration' and 'expansion' interchangeably throughout this paper. Integration in our context refers specifically to building electricity transmission lines that enable the transportation of electricity generated using renewable sources like wind to the demand centers. Such investments in transmission projects would be crucial in order to scale up the share of electricity generated from renewable sources(New York Times 2016).

began in 2010 and all the facilities started service by December 31, 2013. Hence, January 2014 serves as a credible exogenous change to the entire network and is used to analyze the effect of additional transmission on the market clearing price of CRR. Equipped with this quasi-experimental setup, we use a fixed effects model in order to disentangle various kinds of heterogeneity in the effect of transmission integration. We conduct a series of robustness checks to test for the presence of short run dynamics in firm behavior and the exogeneity of the January 2014 as the date of completion of CREZ.

The primary finding of this paper is that CREZ based transmission expansion led to a significant drop in prices of CRRs across all regions and ToUs. However, there exists substantial spatial heterogeneity in the effects of transmission expansion on prices of contracts across West v.s. Other Zones. We find decrease in prices to be most pronounced for CRRs associated with West than for CRRs across other zones in Texas. We find evidence of substantial heterogeneity with respect to the Time of Use aspect of the contracts as well, i.e. the effects of transmission expansion are stronger at Peak than Off Peak hours. The estimated effects are due to a combination of spatial and time varying generation profile of wind energy in the Texas electricity market.

The overall effect of this large scale policy is driven by decrease in market clearing prices for contracts at third and fourth quintile of the distribution. We also find evidence of differential effects across various firm types at different ToUs. Generating firms are found to have the strongest (most negative in magnitude) effect of CREZ based transmission expansion followed by retailers and traders. A policy relevant question is the reason behind the differential effect across firm types? To answer this question we examine the changes in CRR ownership between different locations at different price points by various market participants. We find that the observed heterogeneity is due to different incentives that various firms have in order to hold CRRs either to hedge congestion risks or use them for speculation. These incentives are driven by presence of physical assets like generation facilities for generators, residential and corporate customers in case of retailers, and speculative opportunities in case of financial trading firms.

We present cost estimates of changes in auction expenditures incurred by firms over January 2014 to May 2018 as a result of transmission integration. These estimates are perhaps the first ones in literature that isolate the empirical effect of transmission expansion on aggregate auction expenditures in an electricity market. We find that the drop in CRR prices translate to an aggregate decline in auction expenditure by approximately $261.1 million over January 2014 to May 2018. This amounts to almost 3.8 percent of the total cost (about $6.8 billion) of the CREZ project. The magnitude of these expenditure estimates highlights the close linkage between the transmission infrastructure and the CRR market.

This study contributes to the contemporary literature in several ways. First, this paper presents a detailed empirical analysis of heterogeneity in the effect of transmission integration on the market of CRR. We also estimate spatial, distributional, and firm type (i.e. generators, retailers, and traders) heterogeneity in 'treatment effect' of CREZ. Economists have long been interested in studying the effects of geographical expansion in electricity markets. However, these studies have largely been either theoretical modeling or simulations (Cardell, Hitt, and Hogan 1997; Borenstein, Bushnell, and Stoft 2000; Joskow and Tirole 2000), whereas empirical analyses in this regard have been limited. Recent empirical papers have looked at efficiency effects and competitiveness of wholesale electricity markets as a result of changes in transmission policy and infrastructure (Wolak 2015; Davis and Hausman 2016; Ryan 2017; LaRiviere and Lu 2017; Du and Rubin 2018).

Second, we add to the burgeoning literature on the efficiency of electricity markets due to transmission expansion. We define efficiency as gradual convergence of CRR prices across different locations for various Time of Use (ToU). Narrowing of price differentials across different locations induced by transmission expansion transmission expansion indicates improvement of production efficiency and cost savings while low cost generators are more likely to be dispatched before high cost ones with less frequent and severe transmission congestion. This is associated with significant welfare improvements (Joskow and Tirole 2005). LaRiviere and Lu (2017) provide empirical evidence by estimating transmission congestion loss due to transmission constraints in the Texas electricity market. We address the gap in the literature on the convergence of CRR prices as a result transmission expansion.

Third, our results on price convergence and heterogeneity in the effects of transmission integration are also informative about the efficiency of wholesale electricity market. Convergence of CRR prices across different locations limit the ability of market participants to accrue profits from speculative behavior in the CRR market. This aspect has been analyzed in the economics literature and is a concern amongst policy makers as well (Adamson, Noe, and Parker 2010; Mount and Ju 2014; Leslie 2018; Bushnell, Harvey, and Hobbs 2018). Inefficiency due to quantity constraints has also been found to create arbitrage opportunities that the market participants may exploit in order to profit from the CRR auction (Mount and Ju 2014; Leslie 2018). Another strand of literature looks at the incidence of market power in the generation side and the resulting inefficient allocation and pricing of CRRs (Ito and Reguant 2016; Bushnell 1999; Joskow and Tirole 2000; Borenstein, Bushnell, and Wolak 2002; Borenstein et al. 2008).

The rest of this paper is organized as follows. Section 2 describes the institutional details the Texas electricity market and CREZ transmission expansion. Section 3 describes the data followed by the empirical strategy in Section 4. Results of the baseline specification along with heterogeneity analysis is presented in Section 5. We discuss efficiency of the market in terms of convergence of prices in Section 6. Section 7 reports estimates of auction expenditure and Section 8 concludes.

2 Institutional Details

2.1 Texas electricity market and the CREZ project

The Texas electricity market is one of the largest deregulated electricity markets in the US. As of December 2019, Texas has the largest installed wind capacity of any state in the US. However, the major source electricity generation is natural gas which represents about 52.8 percent of the total generating capacity, followed by wind and coal at 23.3 percent and 14.5 percent respectively (ERCOT 2020). From the consumption side, the residential sector represents the largest share of electricity consumption followed by the commercial sector, and then by the industrial sector (EIA 2019).

A distinctive feature of the Texas electricity market is that it is the only state with a stand-alone grid. The Independent System Operator (ISO) for the electricity market in Texas is the Electric Reliability Council of Texas (ERCOT) and is overseen by PUCT. With over 600 generating units and 46,500 miles of transmission lines, ERCOT is primarily responsible for maintaining the system reliability and managing the competitive wholesale and retail market.

In 2005, Texas legislature passed the Texas Senate Bill 20 which mandated Public Utility Commission of Texas (PUCT) to identify 'Competitive Renewable Energy Zones' in consultation with ERCOT. In 2007, PUCT identified five scenarios based on preliminary transmission analysis and wind generation potential (Bills 2017). After several rounds of analysis by ERCOT, PUCT in 2008, selected 'Scenario 2' which aimed to accommodate 18.5 GW of electric power by building 3,600 circuit miles of 345 kV open-access transmission over 2010 through 2013 and have all facilities in-service by December 31, 2013[4]. As planned, major parts of transmission across regions of Texas were completed by the end of 2013 at a cost of $6.8 billion[5].

The CREZ transmission project has been deemed successful in terms of increasing the integration of wind generation along with elimination of various transmission bottleneck issues, higher reliability, and lowering of wholesale electricity prices (Lasher 2014; Bills 2017). Any change in market expectations about congestion, in theory should be reflected as changes in the market clearing prices of CRRs (Joskow and Tirole 2000; Deng, Oren, and Meliopoulos 2010; Adamson, Noe, and Parker 2010). In what follows, we briefly describe the price formation of CRR in Texas electricity market followed by the determination of CRR payouts. This discussion on institutional details will be helpful to understand the research question that we seek to answer and in interpreting our findings.

4. The selection of 'Scenario 2' amongst the five CREZ scenario was purely based on the goal of reducing transmission congestion and promoting generation of electricity using wind. ERCOT (2008) provides details on the analysis conducted by ERCOT while evaluating the five scenarios. It also provides detailed cost breakdown of transmission lines under these scenarios. The transmission project cost $6.8 billion which was borne by various transmission providers. The benefits accrued to various market participants and ultimately consumers of electricity. Because ERCOT is registered as a "membership-based non-profit 501(c)(4) nonprofit corporation" (ERCOT 2020), it did not stand to gain any profits from CREZ siting.

5. Figure A.1 in Appendix shows various transmission lines built as a part of CREZ along with the their dates of completion.

2.2 The market of Congestion Revenue Rights

2.2.1 Determining market clearing price of CRR

The allocation of CRR in Texas electricity market takes place through various uniform price auctions conducted by ERCOT prior to the realization of DAM. These auctions are held monthly and semi-annually[6]. 90 percent of transmission capacity is available for allocation using monthly auctions. The objective of this auction for ERCOT is to maximize the auction revenue subject to transmission constraints and credit limits. From a market participant's perspective, this auction revenue is basically auction expenditure.

The timing of the auction is as follows:

Step 1. ERCOT posts a CRR network model that basically represents transmission capacity available each month. The CRR network model is derived from network operations model by ERCOT that reflects characteristics of ERCOT transmission system that includes topology, equipment rating, and other operational limits in the system[7].

Step 2. The network model is available to market participants on Market Information System (MIS): 10 business days before the monthly auction and 20 business days before the long term auction sequence.

Step 3. ERCOT then collects bids to buy maximum quantity (in MW) of CRRs and offers to sell available quantity (in MW) of CRRs across different sources and sinks from the market participants.

Step 4. With total transmission capacity[8] and credit limits as constraints, ERCOT maximizes the net auction revenue which is essentially the difference between bid based value and offer based cost. The optimization problem can

6. The long term auctions comprise of six successive auctions with six month windows with one window each month.

7. CRR network model therefore reflects transmission facilities expected to be in-service for the specified month, significant outages, dynamic ratings, monitored elements, contingencies, and settlement points.

8. Transmission constrains across a network are also referred as *simultaneous feasibility constraints* in various competitive electricity markets in the US. For more details refer: Leslie (2018).

be written as:

$$\max_{q_b, q_o} \; [(\textit{bid based value}) - (\textit{offer based cost})]$$
$$s.t. \text{ total transmission capacity} \qquad (1)$$
$$\text{credit limits} \qquad (2)$$

where,

$$\textit{bid based value} = \sum(\text{bid price} \times q_b),$$
$$\textit{offer based cost} = \sum(\text{offer price} \times q_o)$$

The optimization determines the optimal allocation of *cleared bid quantity*, q_b and *cleared offer quantity*, q_o of CRR contracts across various source-sink pairs in the network. The shadow value of transmission constraints (represented by (1) in the optimization problem) across a specific pair of nodes determines the market clearing price ($/MWh) of the CRR contract between those nodes. Shadow price, in this context simply refers to the marginal cost to make an additional increment of transmission capacity (i.e. 1 MW) available. Hence, the shadow price or in other words the market clearing price of CRR is dependent on bids and offers of CRR by various market participants.

Another layer of complexity in the monthly auction design of CRR is due to its treatment of contracts at different ToUs: Peak Weekday (Monday through Friday, 07:00 – 22:00), Peak Weekend (Saturday and Sunday, 07:00 – 22:00), and Off Peak (Monday through Sunday, 01:00 – 07:00 and 23:00 – 24:00). Market participants have an option to submit a single 24 hour bid for all three ToUs in a period t or submit bids for individual ToU[9]. Hence, a bid for an individual ToU is awarded if the bid price exceeds the market clearing price of the CRR at the corresponding ToU. However, a 24 hour bid is awarded if the bid price exceeds the weighted average (by hour) of all three ToU market clearing prices.

Consider a simple numerical example that illustrates this point:

Say a CRR account holder (market participant) enters a 24 hour bid of CRR from source i to sink j at a bid price of $10/MWh for the month of January

9. The occurrence of single 24 hour bids for all ToUs is extremely rare. In our data, single bids account for less than 3 percent of the data. This is confirmed by our correspondence with a CRR market expert.

2019 in a monthly auction[10]. Suppose the market clearing prices of CRR_{ij} for the three ToUs are \$12/MWh, \$8/MWh, and \$4/MWh for Peak Weekday, Peak Weekend, and Off Peak respectively. The weighted average price for the three ToUs is calculated as: $\frac{352\times12+144\times8+248\times4}{744} = \$8.56/\text{MWh}$. Since, the bid price was \$10/MWh, the 24 hour bid is awarded. If the account holder was awarded say 3 MW of CRR at the market clearing prices mentioned above for the month of January 2019, total auction revenue received by ERCOT (or the expenditure for the account holder) for the month of January 2019 is: $3 \times ((352 \times 12) + (144 \times 8) + (248 \times 4)) = \$19,104$.

2.2.2 Determining CRR payout

In Texas electricity market, CRR payout is determined at DAM which is realized one day prior to the real time market. CRR payout is essentially a payment or charge to the CRR holder when transmission grid is congested at DAM. These payouts are characterized by Locational Marginal Price (LMP), which as the name suggests is the cost to serve the next increment (hence, marginal) of Load at an Electrical Bus[11]. Hence, in order to define the CRR payout, it is important to understand how LMP is determined at DAM:

Step 1. ERCOT collects supply offers from various generators in the market. These offers consist of capacity commitments (in MW) at certain prices C_k (\$/MWh) set by generator k.

Step 2. Using the familiar CRR network model and MIS, ERCOT determines transmission constraints and other capacity constraints across the network.

Step 3. With the supply offers and transmission constraints in place, ERCOT runs an optimization problem that minimizes the as-offered costs of supplying electricity subject to transmission constraints, supply meeting the demand,

10. January 2019 had 23 weekdays and 8 weekends implying a total of 744 hours, including: 352 Peak Weekday hours, 144 Peak Weekend hours, and 248 Off Peak hours.

11. An Electrical Bus as defined by ERCOT is simply a physical transmission element that connects using breakers and switches, one or more: Loads, Lines, Transformers, Generators, Capacitors, Reactors, Phase shifters, or Other reactive control devices to the ERCOT Transmission Grid where there is negligible impedance between the connected Transmission Elements. (ERCOT 2018d).

and generator constraints at the DAM. The optimization problem can be written as:

$$
\begin{aligned}
&\min_{Q_k} \sum_k Q_k \times C_k \\
&s.t. \text{ Transmission constraints across the network} && (1)\\
&\quad\;\; \text{Supply = Demand} && (2)\\
&\quad\;\; \text{Generator capacity constraints} && (3)
\end{aligned}
$$

The optimization determines the supply Q_k from each generator $k \in [1, K]$ in the market. The shadow value of the transmission constraints (1) determines the Locational Marginal Price (LMP) for each source/sink in the network. The CRR payout at hour h for a market participant that holds the CRR between source i and sink j is given by:

$$\text{CRR payout (\$/MWh)} = \underbrace{LMP_{j,h} - LMP_{i,h}}_{\text{price swap}}$$

Hence, the total revenue ($) if the market participant holds q_b units of CRR for total number of hours h is:

$$\text{Total Revenue} = q_b \times (LMP_{j,h} - LMP_{i,h}) \times h$$

CRR payout is zero if there is no congestion in the transmission between i and j[12]. However, if there is congestion, CRR payout would be non-zero and the magnitude is determined by the above expression. This difference of LMPs between sink j and source i is called a price swap because the CRR holder receives a payment if $LMP_{j,h} > LMP_{i,h}$ or faces a charge if $LMP_{j,h} < LMP_{i,h}$[13]. Hence, market participants have incentives to purchase CRRs in order to hedge against potential congestion costs at DAM. The following discussion illustrates this idea in detail.

12. Congestion occurs when a transmission line operates at its capacity, for example when a 100MW transmission line carries 100MW of electricity. No congestion is another way of saying that the transmission constraints between a pair of source and sink are slack.

13. In an ideal scenario, we would expect no congestion. However, market imperfections, outages, transmission changes, unanticipated supply or demand shocks may cause congestion and cost increases.

2.2.3 What is the use of CRR?

From the previous sections, it is clear that CRR is essentially a forward contract wherein the forward price is set by the auction and the spot price is determined at the DAM. Hence, like any other forward contract, it can be used to hedge future risks which in this case happens to be congestion of transmission network at DAM.

For simplicity, assume generator k is at source i and retailer r is at sink j. During the settlement of DAM, ERCOT pays generator k : $Q_k \times C_k$ for its electricity and charges the retailer r : $Q_r \times LMP_j$ where Q_r is the amount of electricity demanded by the retailer. Due to congestion, there exists a price wedge and retailer might end up paying higher than what the generator receives for supplying electricity. In order to hedge potential risks of paying high amount of money at DAM, the retailer has incentives to purchase a CRR between source i and sink j at the auction[14].

Using the familiar example presented in Section 2.1, assume that the LMP at DAM between source i and sink j accrued hourly are as follows:

$$\begin{aligned}
\text{Peak Weekday: } \text{LMP}_i^{pwd} &= \$7.4/\text{MWh}, \ \text{LMP}_j^{pwd} = \$24/\text{MWh} \\
\text{Peak Weekend: } \text{LMP}_i^{pwe} &= \$4.6/\text{MWh}, \ \text{LMP}_j^{pwe} = \$17/\text{MWh} \\
\text{Off Peak: } \text{LMP}_i^{off} &= \$2.4/\text{MWh}, \ \text{LMP}_j^{off} = \$2.4/\text{MWh}
\end{aligned}$$

Total revenue for January 2019 for the three ToUs at q_b = 3 MW is:

$$\begin{aligned}
\text{Peak Weekday: } & q_b \times (\text{LMP}_j^{pwd} - \text{LMP}_i^{pwd}) \times 352 = 3 \times (24 - 7.4) \times 352 = \$17,529.6 \\
\text{Peak Weekend: } & q_b \times (\text{LMP}_j^{pwe} - \text{LMP}_i^{pwe}) \times 144 = 3 \times (17 - 4.6) \times 144 = \$5,356.8 \\
\text{Off Peak: } & q_b \times (\text{LMP}_j^{off} - \text{LMP}_i^{off}) \times 248 = 3 \times (2.4 - 2.4) \times 248 = \$0
\end{aligned}$$

$\implies$ Total CRR Revenue = $17,529.6 + 5,356.8 + 0 = \$22,886.4$. Therefore, profits accrued to the CRR account holder over January 2019 = $\$22,886.4 - \$19,104 = \$3,782.4$.

14. This is a simplified scenario that is meant to show how CRR is useful as a hedging instrument. Retailer(s) may also purchase CRRs across points different than the ones it is purchasing electricity from. A similar argument holds for generators as well. They also have incentives to purchase CRRs in order to hedge potential risks.

As evident from the above discussion and the simplified example, CRR essentially acts as a hedging instrument for the contract holder because it prevents them against potential congestion risks at DAM. Having said that, various market participants may use CRR as a speculative device in order to profit from congestion between a pair of nodes in the network. Ideally, if the transmission feasibility constraints are not violated (or the set of contracts are simultaneously feasible) then the equilibrium allocation of contracts determined at the auction matches the realized flow of electricity in the market at DAM, hence the CRR payouts would equal to the auction revenue (Hogan 1992). However, unforeseen transmission outages, supply shocks, arbitrage opportunities as a result of private information and quantity constraints might lead to CRR payouts being higher than the auction expenditure. This is seen as a potential market inefficiency and has been a source of interest among researchers and a point of concern for policy makers (CAISO 2016; Bushnell, Harvey, and Hobbs 2018; Leslie 2018).

3 Data

This paper uses market clearing data on monthly auctions of CRR over December 2010 – May 2018. The dataset is compiled from data on market clearing information of CRR contracts obtained from ERCOT. The auction data comprises of market clearing price ($/MWh) determined by the ERCOT in a uniform price auction as described in the previous section. Along with prices, a CRR contract includes details on contract type (obligation/option), ToU (Peak Weekday, Peak Weekend and Off Peak), quantity of contracts expressed in MW and source (i) and sink (j). For the analysis in this paper, we focus on Obligation type CRRs between Hubs and Load Zones across West, North, South, and Houston[15].

In order to prepare the data for the analysis, we first separate the dataset for

15. ERCOT defines 'Hub' as a designated settlement point consisting of Hub Bus or group of Hub Buses. A Hub Bus in power engineering is an energized electrical Bus or a group of energized electrical Bus. Hence, the market clearing prices at Hubs is essentially a simple average of clearing prices at particular 345kV stations in a zone. The sample consists of following Hubs: North, West, South, Houston, ERCOT Hub Average, and ERCOT Bus Average. 'Load Zone' are defined as a group of electrical buses assigned to the same zone. Every electrical Bus in ERCOT with a Load must be assigned to a Load Zone for settlement purposes. Hence, Load Zones are Load distribution factor weighted averages of Load buses in a zone. The sample consists of following Load Zones: North, West, South, Houston, LCRA, RAYBN, AEN, and CPS. Load Zones LCRA, RAYBN, AEN, and CPS are part of South Zone whereas RAYBN is part of North Load Zone. (ERCOT 2018d).

Obligation type CRRs with positive market clearing prices. The contracts with negative market clearing prices are called 'Counterflow CRRs'. However, in case of ERCOT, counterflow CRRs can be treated as regular CRRs with positive price by flipping the Source and Sink and interpreting them as a Sell contract[16]. This is greatly helpful as it almost doubles our sample size and provides more variation in the data to identify the effect of transmission shock. Next, we aggregate the quantities (MW) of identical CRR contracts wherein identical contracts are defined as the ones with the same source, sink, ToU, time period (month-year), and market clearing price ($/MWh). We then subset the dataset with the observations wherein the source and sink is either a Hub or a Load Zone. Since, the effect of transmission shock might differ across ToUs because of variability in wind production at Peak v.s. Off Peak, we separate the sample for Peak Weekday, Peak Weekend, and Off Peak. This leaves us with 3367, 3266, and 3268 monthly observations from December 2010 through May 2018 for Peak Weekday, Peak Weekend, and Off Peak CRRs respectively.

Table 1 presents summary statistics for CRR market clearing prices for the three samples before and after completion of CREZ in January 2014. There is a decrease in mean prices for Peak Weekday, Peak Weekend and Off Peak contracts. The drop in standard deviation of prices across the three ToUs reflects a decrease in variability of prices post CREZ transmission integration. In the analysis that follows, we identify if this decrease in mean prices is indeed attributable to the addition in transmission due to CREZ. To obtain a better sense of the underlying pattern, we plot the monthly price averages of CRR contracts for three ToUs in Figure 1. As evident, there is a noticeable drop in prices post January 2014, when the extra transmission was brought in service. The drop in average prices is most pronounced for contracts at Peak Weekday and Peak Weekend, followed by Off Peak.

4 Empirical Model

The empirical analysis in this paper aims at identifying the effect of transmission expansion on the market clearing price of CRR contracts for the three times of

16. For a greater exposition on counterflow Financial Transmission Rights refer Adamson, Noe, and Parker (2010).

Table 1: Summary Statistics of CRR market clearing price ($/MWh)

	Peak Weekday		Peak Weekend		Off Peak	
	Mean (Std. Dev.)	#	Mean (Std. Dev.)	#	Mean (Std. Dev.)	#
Pre January 2014	2.089 (3.309)	967	1.626 (2.810)	942	1.158 (2.089)	944
Post January 2014	1.834 (2.034)	2400	1.466 (1.766)	2324	0.683 (0.747)	2324

Notes:
The table denotes mean and standard deviation of CRR market clearing prices for Peak Weekday, Peak Weekend, and Off-Peak contracts before and after CREZ transmission integration in January 2014. N denotes the number of observations in both categories.

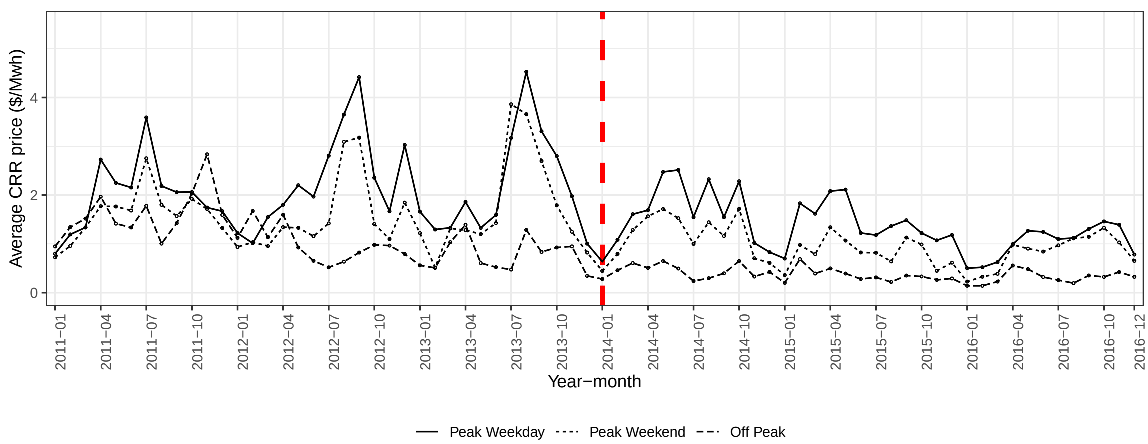


Figure 1: Monthly price averages of Peak Weekday, Peak Weekend, and Off Peak CRR contracts. Dashed vertical line marks transmission integration: January 2014.

use. We use fixed effects estimator to estimate the within variation in source and sink after controlling for a rich set of control variables. We estimate the following baseline specification using a fixed effects model for the sample of Peak Weekday, Peak Weekend, and Off Peak CRR contracts.

$$\mathrm{CRR}_{ij,t} = \beta_0 + \beta_1 \cdot D_{t\geq 01-2014} + \beta_2 \cdot D_{t\geq 01-2014} \times trend + \mathbf{X}'_{ij,t}\Pi + \epsilon_{ij,t} \qquad (1)$$

where, $\mathrm{CRR}_{ij,t}$ is the market clearing price ($/MWh) of a CRR contract between source i and sink j at period t. The treatment effect variable is the binary indicator $D_{t\geq 01-2014}$ equal to one for every month post January 2014 and zero for months prior to January 2014. In order to capture the effect of transmission expansion on the trend of dependent variable we estimate the interaction of $D_{t\geq 01-2014}$ with a linear time trend[17]. We refer to the corresponding parameter estimate $\hat{\beta}_2$ as treatment trend effect in the ensuing discussions[18].

In order to control for confounding factors, we use a rich set of fixed effects summarized by the vector $\mathbf{X}_{ij,t}$. We include a linear time trend t and fixed effects for source (η_i) and sink (η_j). These fixed effects ensure that β_1 and β_2 are estimated by the within variation in prices of CRR contracts across source i and sink j. To account for potential endogeneity due to seasonality, we use month fixed effects (θ_m), source by month $(\eta_i \times \theta_m)$ and sink by month $(\eta_j \times \theta_m)$ fixed effects. The empirical specification also includes fixed effect for 2017 (δ_{2017}) to control for the price spike as a result of massive floods in Texas due to hurricane Harvey in 2017 (Chokshi and Astor 2017). Because the market clearing price is determined as a result of a monthly auction one might suspect errors in Equation 1 to be correlated within the sample month. To mitigate that concern, the paper reports robust standard errors clustered at year-month level.

The identifying assumption is that the unobserved determinants of CRR price included in the error term $\epsilon_{ij,t}$ do not change discontinuously post transmission integration in January 2014. A potential threat to identification is the presence of regulatory changes in transmission policy or unobserved price shocks that could be correlated with the timing of CREZ based transmission integration. This would lead to the familiar omitted variable bias and hence the parameters of interest would loose their causal interpretation. However, based on our research we do not find occurrence of such a policy and we utilize a battery of fixed effects to control for any source and sink specific structural and seasonal factors that could be a threat to identification.

Another concern is the possibility of short-run dynamics in firm behavior around the period when transmission network was expected to go in service. This is to say that market participants altered their bidding behavior in anticipation of the policy change (transmission expansion in our case) in January 2014. We test for the presence of such behavior by using a strategy wherein we exclude observations for time periods near the treatment date. This is similar in spirit to

17. Following Chimeli and Soares (2017) we specify *trend* to be equal to zero in the first month of treatment.

18. Refer to Figure A.2 in Appendix for a graphical intuition about the signs of coefficient of interest $\hat{\beta}_1$ and $\hat{\beta}_2$ in Equation 1.

the 'Donut RD' approach introduced by Barreca, Lindo, and Waddell (2016). In Section 5.1, we present comparisons of our baseline results with robustness checks using different windows of excluding observations before and after January 2014.

5 Results

This section provides results for the effect of CREZ transmission integration on the market clearing prices of CRR. We begin by presenting baseline results for Equation 1 and robustness checks followed by a detailed analysis of potential spatial, distributional, and firm specific heterogeneity. We also discuss potential mechanisms that might be driving the obtained results.

5.1 Baseline Results and Robustness Checks

Table 2 presents the estimation results of Equation 1 along with the results of robustness checks for short-run firm dynamics. As evident from estimates of Base Model in Table 2, the transmission expansion led to a drop in CRR prices across all the three ToUs. The drop in prices is largest in magnitude for Peak Weekday ($0.915/MWh) and Peak Weekend ($1.049/MWh) followed by Off Peak ($0.326/MWh). We do not find a strong interaction effect of treatment and trend for contracts at Peak Weekday and Peak Weekend. However, this interaction effect is positive and statistically significant in case of Off Peak contracts. The magnitude of the coefficient $\hat{\beta}_2$ suggests that the on an average, Off Peak prices rose by $0.038/MWh each month post January 2014. As we discuss later, the positive estimate of treatment trend effect for Off Peak CRR is linked with the wind generation profile at Off Peak in Texas[19].

We conduct robustness checks to test short-run firm dynamics wherein we estimate Equation 1 by excluding observations before and after 1 month, 2 months, and 3 months from January 2014[20]. We notice from Table 2 that the point estimates of β_1 for robustness checks are statistically similar to the Base Model for

19. Robustness results of baseline specification Equation 1 with different combinations of fixed effects are included in the Appendix.

20. A potential concern could be existence of long run strategic behavior which is not addressed by this strategy. We do not expect such behavior to be a cause of concern for monthly auctions as firms are likely to respond to short run changes in congestion in this particular setting. We could, however, expect longer run changes in semi-annual and annual auctions.

Table 2: Regression results for Peak Weekday, Peak Weekend, and Off Peak CRR

Peak Weekday	Base Model	1 Month	2 Months	3 Months
	(1)	(2)	(3)	(4)
$D_{t\geq 01-2014}$	-0.915^{***}	-1.029^{***}	-1.074^{***}	-1.193^{***}
	(0.300)	(0.319)	(0.348)	(0.373)
95% Confidence Interval	[−1.503, −0.327]	[−1.654, −0.404]	[−1.756, −0.392]	[−1.924, −0.462]
$D_{t\geq 01-2014} \times trend$	−0.016	-0.021^{*}	−0.022	−0.023
	(0.012)	(0.012)	(0.013)	(0.014)
Observations	3367	3298	3247	3187
Peak Weekend	Base Model	1 Month	2 Months	3 Months
	(5)	(6)	(7)	(8)
$D_{t\geq 01-2014}$	-1.049^{***}	-1.164^{***}	-1.272^{***}	-1.401^{***}
	(0.286)	(0.312)	(0.335)	(0.357)
95% Confidence Interval	[−1.609, −0.488]	[−1.775, −0.552]	[−1.929, −0.615]	[−2.101, −0.701]
$D_{t\geq 01-2014} \times trend$	−0.002	−0.003	−0.004	−0.005
	(0.011)	(0.012)	(0.013)	(0.014)
Observations	3266	3197	3149	3096
Off Peak	Base Model	1 Month	2 Months	3 Months
	(9)	(10)	(11)	(12)
$D_{t\geq 01-2014}$	-0.326^{***}	-0.339^{***}	-0.369^{***}	-0.370^{**}
	(0.116)	(0.125)	(0.134)	(0.149)
95% Confidence Interval	[−0.553, −0.099]	[−0.584, −0.094]	[−0.632, −0.106]	[−0.660, −0.078]
$D_{t\geq 01-2014} \times trend$	0.038^{***}	0.039^{***}	0.040^{***}	0.040^{***}
	(0.006)	(0.007)	(0.007)	(0.007)
Observations	3268	3206	3152	3094

Notes:
The dependent variable is CRR market clearing price for all the three samples. The variable of interest $D_{t\geq 01-2014}$ is an indicator variable marking the completion of CREZ in January 2014. 'Base Model' includes all observations whereas '1 Month', '2 Months', and '3 Months' drop observations before and after 1, 2, and 3 months of January 2014. All specifications control for time trend t, source fixed effects (η_i), sink fixed effects (η_j), seasonality, and fixed effect for the year 2017. Robust standard errors, clustered at year-month level are presented in parenthesis. Significance: *p<0.1; **p<0.05; ***p<0.01

all the three ToUs. This is confirmed due to the overlapping 95 percent confidence intervals of these estimates. The results of robustness checks allow us to rule out the possibility of bias in our results due to change in behavior of market participants in anticipation of transmission integration in January 2014.

Another concern could be the timing of the transmission expansion. Recall, that CREZ based transmission lines were built over 2010 to 2013. Even though most of the construction was completed at different points in 2013, we might see changes due to transmission expansion reflected in CRR prices before January 2014. In order to address this concern we present two robustness checks. First, we conduct an event style analysis that compares the changes in CRR prices in each year. Specifically, we estimate:

$$\mathrm{CRR}_{ij,t} = \alpha_0 + \sum_{k=2010}^{2018} \alpha_k \cdot 1\left[\tau = k\right] + t + \eta_i + \eta_j + \omega_{ij,t} \tag{2}$$

To allow identification of α_k, we drop month fixed effects and their interactions with Source and Sink fixed effects. Further, we normalize $\alpha_{2013} = 0$. Figure 2 presents the coefficient estimates of α_k for Peak Weekday. Peak Weekend, and Off-Peak. As shown in Figure 2, the coefficient estimates are positive statistically indistinguishable from zero for Peak weekday and Peak Weekend, and marginally significant at 5 percent critical level for Off-Peak sample for the years preceding 2013. We see a negative and statistically significant effect post 2013 for all the three samples and remains negative through 2018.

A potential concern could be that the estimates from the baseline specification could be underestimates and the effect might be progressive over 2013 as various parts of the transmission network was completed throughout 2013. While this is a valid concern, we check if the effects were realized in 2013 by estimating a specification similar to Equation 1 which includes a binary variable and a continuous trend term for 2013. The results of this estimation along with the baseline estimates are reported in Table 3 for the three samples. The coefficient estimates associated with progressive CREZ effect are found to be statistically insignificant for both Peak Weekday and Weekend. In case of Off Peak the estimates are significant at 10 percent critical level. However, these estimates are jointly insignificant at 5 percent critical level for all the three samples as indicated by the Robustness F-stat (p-val) presented in Table 3. Therefore, there isn't convincing statistical evidence for a progressive effect of CREZ on CRR prices and the baseline results can be thought of as conservative estimates under the assumption that the effects were realized post 2013.

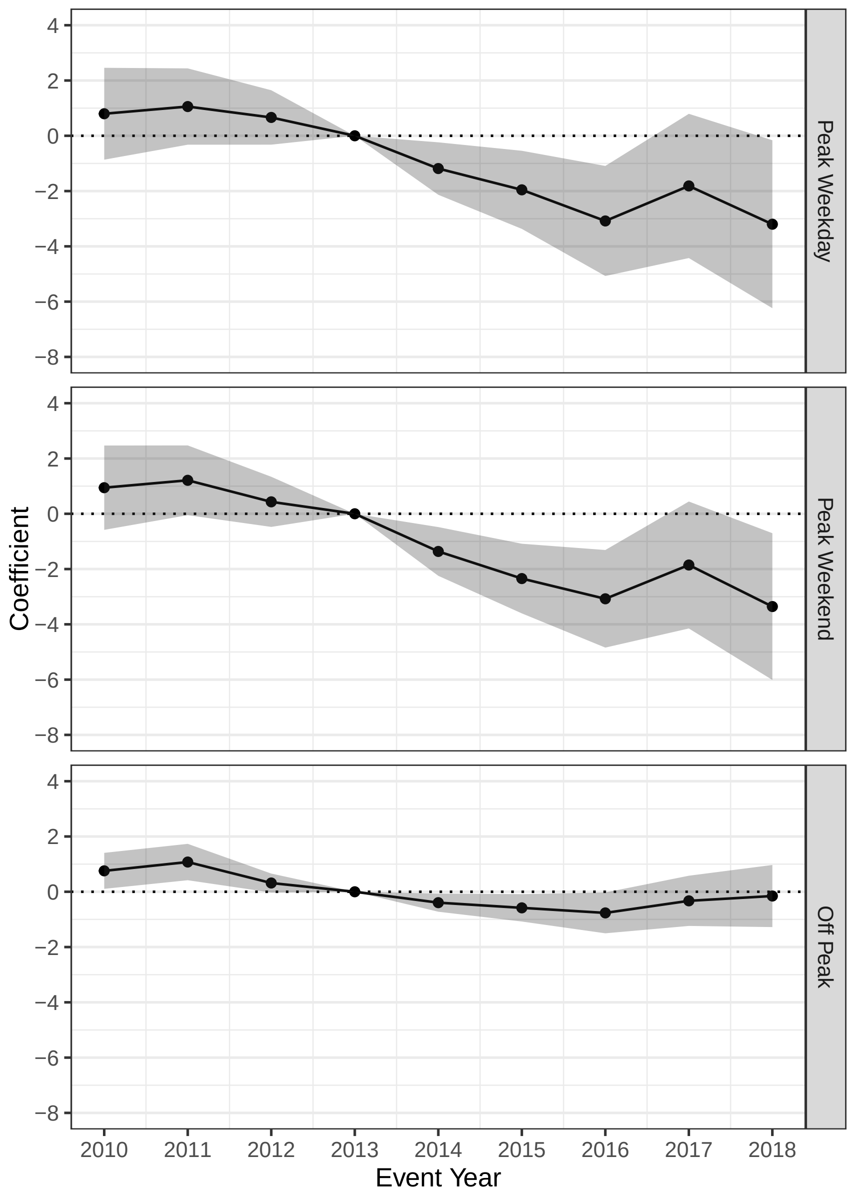


Figure 2: Estimates of the event analysis in Equation 2

5.2 Spatial heterogeneity in the effects of CREZ transmission integration

Due to spatial nature of CREZ, it is of interest to distinguish the effect amongst different regions of Texas. Because one of the primary goals of CREZ was to integrate the wind generation from West to other regions of the state, we might expect effect of the transmission expansion to be different for contracts associated with West than for those traded between other regions. We estimate the baseline

Table 3: Robustness check for progressive effect of CREZ on CRR prices

	Time of Use					
	Peak Weekday		Peak Weekend		Off Peak	
	(1)	(2)	(3)	(4)	(5)	(6)
$D_{y=2013}$		-0.668		-0.392		-0.318^{*}
		(0.484)		(0.428)		(0.173)
$D_{y=2013} \times trend$		0.017		0.047		0.039^{*}
		(0.058)		(0.050)		(0.021)
$D_{t\geq 01-2014}$	-0.915^{***}	-1.476^{**}	-1.049^{***}	-1.147^{**}	-0.326^{***}	-0.406^{**}
	(0.300)	(0.580)	(0.286)	(0.460)	(0.116)	(0.196)
$D_{t\geq 01-2014} \times trend$	-0.016	-0.035^{*}	-0.002	-0.005	0.038^{***}	-0.036^{***}
	(0.012)	(0.020)	(0.011)	(0.016)	(0.006)	(0.008)
Robustness F-stat		2.322		1.001		1.772
(p-val)		0.098		0.367		0.170
Observations	3367	3367	3266	3266	3268	3268

Notes:

The dependent variable is CRR market clearing price for all the samples. $D_{y=2013}$ is an indicator variable that is 1 for observations in the year 2013. $D_{t\geq 01-2014}$ is an indicator variable marking the completion of CREZ in January 2014. Columns (1), (3), and (5) replicate the estimates from the baseline specification Equation (1). Columns (2), (4), and (6) are the robustness specifications to check for the progressive effects of CREZ expansion. Robustness F-stat (p-val) is for the null hypothesis that the estimates for $D_{y=2013}$ and $D_{y=2013} \times trend$ are jointly equal to zero. All specifications control for time trend t, source fixed effects (η_i), sink fixed effects (η_j), seasonality, and fixed effect for the year 2017. Robust standard errors, clustered at year-month level are presented in parenthesis. Significance: *p<0.1; **p<0.05; ***p<0.01

specification with the addition of an indicator variable specifying whether the contract has source or sink at West for Peak Weekday, Peak Weekend, and Off Peak. The results of this estimation are reported in Table 4. We see the effect of transmission expansion to be almost three times for CRRs associated with West than for other CRRs at Peak Weekday and Peak Weekend. The estimates for treatment trend imply that on an average prices of contracts at West decreased approximately $0.044/MWh per month post transmission shock at Peak Weekday and Peak Weekend. Interestingly, the results are quite different in case of Off Peak wherein we notice a positive and statistically significant effect of transmission integration on non-West CRRs. However, the effect is about $2.743/MWh lower for West CRRs than CRRs across other regions.

Another result that warrants attention is the positive estimate of treatment

Table 4: Comparison of treatment effect for contracts with source and/or sink at West v.s. Other regions

	Time of Use		
	Peak Weekday	Peak Weekend	Off Peak
	(1)	(2)	(3)
$D_{t\geq 01-2014}$	-0.515^{**}	-0.598^{***}	0.437^{***}
	(0.258)	(0.225)	(0.133)
$\times$ *trend*	-0.0003	0.010	0.039^{***}
	(0.011)	(0.010)	(0.006)
$D_{t\geq 01-2014} \times \mathbb{1}\{\text{West}\}$	-1.323^{***}	-1.483^{***}	-2.743^{***}
	(0.510)	(0.443)	(0.336)
$\times$ *trend*	-0.044^{***}	-0.037^{***}	0.010^{**}
	(0.010)	(0.008)	(0.004)
Observations	3367	3266	3268
R^2	0.423	0.418	0.486

Notes:

The dependent variable is CRR market clearing price for all the three samples. The variable of interest $D_{t\geq 01-2014}$ is an indicator variable marking the completion of CREZ in January 2014. All specifications control for time trend t, source fixed effects (η_i), sink fixed effects (η_j), seasonality, and fixed effect for the year 2017. Robust standard errors, clustered at year-month level are presented in parenthesis. Significance: *p<0.1; **p<0.05; ***p<0.01

trend effect for Off Peak CRRs[21]. A potential reason for this finding is attributed to wind generation profile in Texas. Most of the wind based electricity generation occurs during Off Peak hours or during periods of low demand (Potomac Economics 2019). Share of electricity generated through wind in Texas has been on an increasing trend over the years and is most significant at Off Peak (ERCOT 2018a). Higher wind production at Off Peak is linked with higher market expectation for congestion due to limited transmission capacity and this is reflected as a positive treatment trend estimate in CRR prices.

To further investigate the differential effect of transmission integration on CRR at different Source - Sink pairs, we estimate a much more flexible version of baseline specification Equation 1 wherein we include interaction of treatment with

21. The estimate for treatment trend for non-West CRRs is \$0.039/Mwh and \$0.049/MWh (0.039+0.010) for West CRRs.

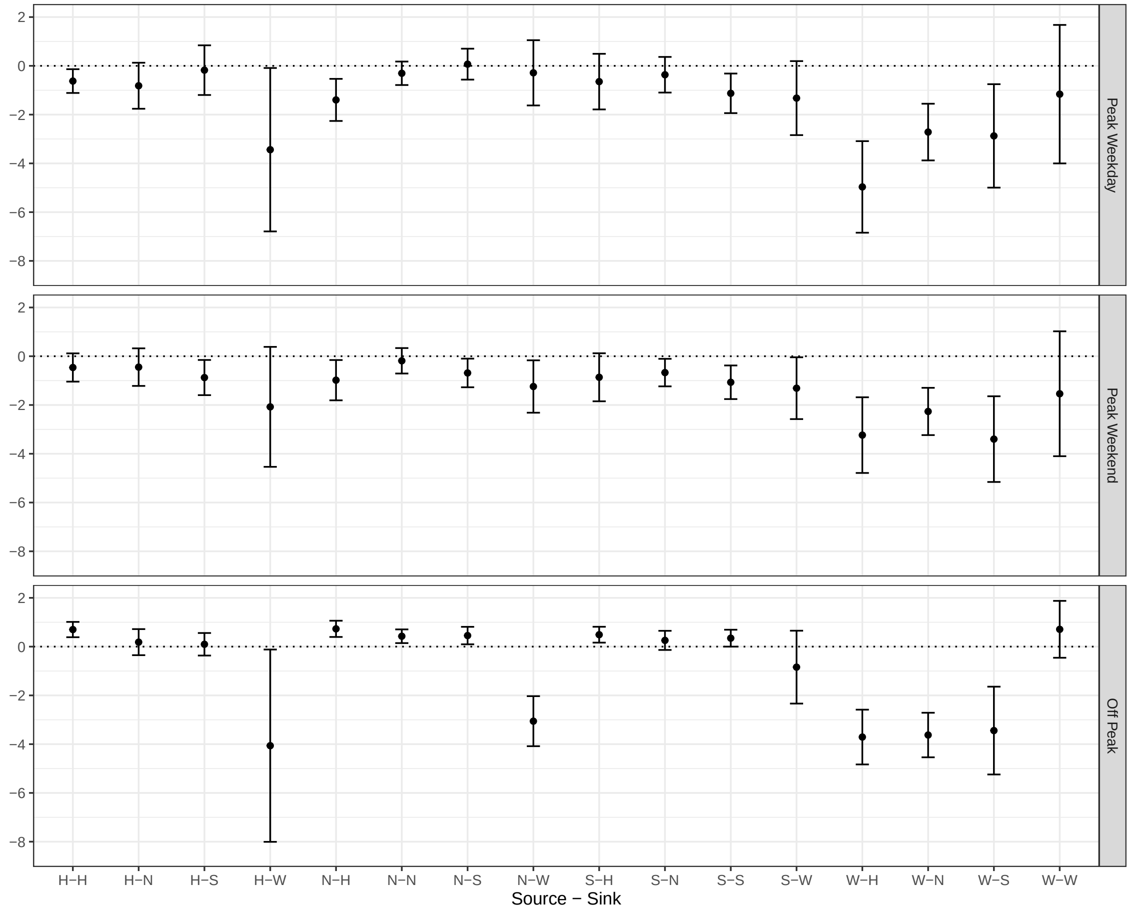


Figure 3: Estimates of treatment effect for different Source Sink pairs for CRRs at Peak Weekday, Peak Weekend, and Off Peak

indicator variables denoting the Source-Sink pair of a CRR[22].We report the estimates for all these interaction variables along with their 95 percent confidence intervals for Peak Weekday, Peak Weekend, and Off Peak in Figure 3.

Substantial heterogeneity in estimates of treatment effect for different location pairs can be observed from Figure 3. However, there is also some similarity across Peak Weekday and Peak Weekend where we see coefficient estimates to be negative across all the pairs. However, the effect is strongest for CRRs with Sources at West Hub/Load Zone and Sinks at Houston, North, and South. CRRs with Sink at West do not necessarily display this pattern with the exception of Houston – West pair which is statistically significant at 5 percent critical level for Peak

22. In sum there are 16 Source-Sink combinations and thus 16 relevant interaction terms. We estimate separate intercepts for all the 16 groups of CRRs along with interaction with trend variable.

Weekday and Off Peak. Estimates for Off Peak sheds details about the estimate on differential effect of CREZ on non-West CRRs reported in Table 4. Here, the point estimates are negative only for CRRs with Source or Sink at West (except for W-W which is positive but statistically indistinguishable from zero). These estimates are similar in magnitude to those for Peak hours, however because non-West pairs are positive and statistically significant, the overall average effect at Off Peak is found to be economically small as reported in Table 2.

The results obtained from this analysis show that CREZ transmission expansion from West to major demand centers like Houston and South of Texas led to substantial lowering of expectation of congestion at DAM across ToU. It is interesting to note that certain estimates for demand region pairs like North – Houston, South – North, and South – South are also negative and statistically significant for Peak hours. This is an evidence of the spillover effect of CREZ transmission infrastructure and the fact that these transmission lines are open access, i.e. the use is not limited to just wind energy. This implies that CREZ not only reduced expected congestion between West and other zones but also between these other zones.

5.3 Distributional heterogeneity in the effects of CREZ transmission integration

The analysis of spatial heterogeneity in the previous subsection finds a strong effect of transmission expansion for contracts associated with West region. However, it would be interesting to see if there exists some distributional pattern. To explore this we classify different location-pairs of CRRs into four quintiles based on average market clearing prices from December 2010 to December 2013. Restricting the time period to December 2013 avoids the issue of treatment affecting the assignment of a CRR into a specific quintile. All the contracts in the dataset are then assigned the quintile corresponding to their location pair[23].

We estimate a specification similar to Equation 1 with the addition of inter-

23. We conduct robustness checks by using a series of different definitions of quintile windows, i.e. we use December 2010 – June 2013, December 2010 – December 2012, and December 2010 – June 2012 to define the quintiles of CRRs. The parameter estimates are found to be statistically similar for most of the definitions for all ToUs. The results of these specifications are provided in Appendix.

Table 5: Regression results for distributional heterogeneity in the effect of transmission integration

	Time of Use		
	Peak Weekday	Peak Weekend	Off Peak
	(1)	(2)	(3)
$D_{t\geq 01-2014}$ × Quintile 1	-0.415^{*}	-0.441^{*}	0.532^{***}
	(0.240)	(0.244)	(0.156)
$D_{t\geq 01-2014}$ × Quintile 2	-0.176	-0.462^{*}	0.385^{***}
	(0.274)	(0.243)	(0.142)
$D_{t\geq 01-2014}$ × Quintile 3	-1.218^{***}	-1.292^{***}	0.102
	(0.350)	(0.302)	(0.227)
$D_{t\geq 01-2014}$ × Quintile 4	-2.561^{***}	-2.954^{***}	-3.337^{***}
	(0.919)	(0.901)	(0.466)
Observations	3367	3266	3268
R^2	0.441	0.438	0.504

Notes:
The dependent variable is CRR market clearing price for all the three samples. $D_{t\geq 01-2014}$ is an indicator variable marking the completion of CREZ in January 2014. Quintile i specifies whether a CRR contract belongs to ith quintile location-pair based on average clearing price over December 2010 – December 2013. All specifications control for time trend t, source fixed effects (η_i), sink fixed effects (η_j), seasonality, and fixed effect for the year 2017. Robust standard errors, clustered at year-month level are presented in parenthesis. Significance: *p<0.1; **p<0.05; ***p<0.01

action between treatment dummy and indicator variables specifying whether the contract belongs to quintile i. The results of this estimation for the three ToUs are reported in Table 5. The estimated effect is strongest for CRRs with location pairs in the fourth quintile followed by the contracts in the third quintile, though the estimate for third quintile is positive but statistically insignificant for Off Peak sample. However, certain differences across ToUs also emerge. We observe a positive effect in case first and second quintile for Off Peak CRRs. Both of these groups comprise of location pairs that have a positive treatment effect as observed from Figure 3.

These results imply that the baseline estimates obtained in Table 2 are driven by drop in prices of contracts at upper quintiles. It also provides another perspective on why we observe the overall treatment effect for Off Peak contracts to be only about -$0.326/MWh. The primary reason is that fourth quintile is dominated by contracts across West which offsets the positive effect estimated for contracts at lower quintiles that basically comprise of CRRs across other regions. The composition of the upper two quintiles for the three ToUs is dominated by contracts across West which also provides a direct link between these results and the ones obtained for spatial heterogeneity in the previous subsection[24].

5.4 Heterogeneity in the effect of transmission integration on different market participants

One of the major sources of heterogeneity in the Texas electricity market is the participation of different kinds of firms in CRR auction. As discussed in Section 2.3.3, firms have varied incentives to hold CRRs which could be an additional source of heterogeneity in the effect of transmission expansion. This is to say that CRRs held by different kinds of market participants (like generators, retailers, and financial traders) may exhibit variation in the extent of effect of transmission expansion on the market clearing prices. Studying this heterogeneity might be insightful into the behavior of various market participants in the market. To explore this we classify each CRR account holder into three broad categories: Generating firms, Retailing firms, and Financial trading firms[25]. The CRR contracts are then aggregated based on market clearing price, source, sink, time period, and firm type. This leaves us with 4853, 4657, and 4670 observations of distinct CRR contracts for Peak Weekday, Peak Weekend, and Off Peak respectively.

As summarized in Table 6, we observe a similar ownership pattern of CRRs for the firm types across the three ToUs. Traders held approximately 37 – 40 percent of CRRs (MW) post January 2014 followed by Generators who held about 30 percent of contracts across the ToUs. The increase in share of CRRs held by both generators and traders is driven by substantial decrease in share of retailers across the ToUs. Further, we observe a clear decline in market clearing price post transmission integration for all three firm types across Peak Weekday, Peak Weekend,

24. CRRs with Source and/or Sink at West make about 62, 59, and 63 percent of total observations in third and fourth quintile for Peak Weekday, Peak Weekend, and Off Peak in the data respectively.

25. Details on the classification and the firms in each category is summarized in Appendix.

Table 6: Summary Statistics of CRR market clearing price ($/MWh) by firm type

Peak Weekday	Generator		Retailer		Trader	
	Mean	Share(%)	Mean	Share(%)	Mean	Share(%)
Pre January 2014	2.540	25.72	2.101	44.30	2.143	29.98
Post January 2014	2.177	29.63	1.745	33.56	1.511	36.81
Peak Weekend	Generator		Retailer		Trader	
	Mean	Share(%)	Mean	Share(%)	Mean	Share(%)
Pre January 2014	1.934	27.00	1.375	45.74	1.666	27.26
Post January 2014	1.796	31.38	1.288	31.83	1.131	36.79
Off Peak	Generator		Retailer		Trader	
	Mean	Share(%)	Mean	Share(%)	Mean	Share(%)
Pre January 2014	1.005	23.32	0.727	49.65	1.143	27.03
Post January 2014	0.660	30.05	0.549	29.95	0.491	40.00

Notes:
The classification of CRR account holders as Generator, Retailer, and Trader is explained in Appendix. Total number of observations for Peak Weekday, Peak Weekend, and Off Peak CRRs is 4853, 4657, and 4670 respectively. Share (%) refers to the percentage of CRR contracts (MW) owned by a specific firm type at a particular ToU before and after transmission integration in January 2014.

and Off Peak. The decrease in clearing price could be driven by different bidding strategies and location specific ownership patterns of different firms. In order to identify the differential effect of CREZ based transmission expansion on CRR clearing prices for different firm types, we estimate firm specific treatment and trends in the baseline specification Equation 1.

Table 7 reports the estimation results for the three ToUs. The parameter estimates show a negative and statistically significant effect of transmission integration on market clearing prices for all the three firm types across the three ToUs with the exception of Retailers at Off Peak. However, the average decrease in prices is strongest in magnitude for generating firms. This decrease is found to be $1.999/MWh for Peak Weekend followed by Peak Weekday and Off Peak where the average decrease in approximately $1.808/MWh and $0.407/MWh respectively. We do not find substantial difference in the treatment effect for Off Peak contracts, indicating that the differential effect of transmission integration

Table 7: Regression results for firm type heterogeneity in the effect of transmission integration

	Time of Use		
	Peak Weekday	Peak Weekend	Off Peak
	(1)	(2)	(3)
$D_{t\geq 01-2014} \times \mathbb{1}\{\text{Generator}\}$	-1.808^{***}	-1.999^{***}	-0.407^{***}
	(0.459)	(0.413)	(0.144)
$\times$ *trend*	-0.033^{**}	-0.003	0.041^{***}
	(0.015)	(0.012)	(0.006)
$D_{t\geq 01-2014} \times \mathbb{1}\{\text{Retailer}\}$	-1.519^{***}	-1.171^{***}	-0.072
	(0.423)	(0.325)	(0.108)
$\times$ *trend*	-0.040^{***}	-0.019	0.039^{***}
	(0.015)	(0.012)	(0.006)
$D_{t\geq 01-2014} \times \mathbb{1}\{\text{Trader}\}$	-1.254^{***}	-1.112^{***}	-0.309^{***}
	(0.345)	(0.296)	(0.106)
$\times$ *trend*	-0.040^{***}	-0.023^{*}	0.031^{***}
	(0.014)	(0.012)	(0.005)
Observations	4853	4657	4670
R^2	0.369	0.345	0.313

Notes:
The dependent variable is CRR market clearing price for all the three samples. $D_{t\geq 01-2014}$ is an indicator variable marking the completion of CREZ in January 2014. $\mathbb{1}\{\text{Generator}\}$ equals one if CRR is owned by a generating firm, $\mathbb{1}\{\text{Retailer}\}$ equals one if the CRR is owned by a Retailer and $\mathbb{1}\{\text{Trader}\}$ equals one if the CRR is owned by a Financial trading firm. All specifications control for time trend t, source fixed effects (η_i), sink fixed effects (η_j), seasonality, and fixed effect for the year 2017. Robust standard errors, clustered at year-month level are presented in parenthesis. Significance: *p<0.1; **p<0.05; ***p<0.01

was pretty muted across market participants.

However, this is in contrast to what we observe for Peak Weekday and Peak Weekend contracts. Specifically, compared to generators we find that the treatment effect is lower in magnitude for retailers at Peak Weekday and Peak Weekend and is lowest for financial trading firms. This differential effect is perhaps highest at Peak Weekend wherein the treatment effect is lower by almost $0.9/MWh for retailers and traders compared to generators. However, in case of Peak Weekday, the estimate for generators is \$0.3/MWh lower than that of retailers, which in turn is lower by about \$0.3/MWh than traders. These estimates highlight existence of significant differences in how generators behave in the market compared to retailers and traders. Finally, we see consistent pattern of trend estimate across the firms and ToUs. As expected, the trend is positive at Off Peak and negative at Peak Weekday. The magnitude is similar across the firm types which is not surprising. To investigate the observed differences in these estimates across the firms we explore mechanisms that answer two questions. First, do firms differ in their spatial ownership of CRRs? Second, do firm differ in their ownership of CRRs at different points of the price distribution? The answers to these questions would be helpful to understand the reasons behind the firm specific heterogeneity.

5.4.1 Mechanisms driving firm type heterogeneity

To better understand the results summarized in Table 7, it is essential to recognize how various market participants differ in their ownership of CRRs in the market. To that end we provide descriptive evidence in the form of heat-maps to highlight two potential mechanisms – location specific ownership and ownership of CRR at different points in the price distribution. These heat-maps are represented as a 3×3 matrix of 9 smaller heat-maps with firm type along the columns and ToU along the rows.

A. Changes in ownership across location pairs:
Each of the 9 smaller heat-maps in Figure 4 are themselves a 16×9 matrix with locations pairs as rows and years as columns. These cells measure the percentage share of CRRs given by:

$$\% \text{ of CRRs} = \frac{q^f_{l,y,T}}{\sum_f q^f_{l,y,T}} \times 100 \tag{3}$$

where, $q^f_{l,y}$ is the quantity of CRRs (in MW) owned by a firm type $f \in \{$Generator, Retailer, Trader$\}$ between location pair $l \in \{$W-W, W-S, W-N, W-H, S-W, S-S, S-N, S-H, N-W, N-S, N-N, N-H, H-W, H-S, H-N, H-H$\}$ at ToU $T \in \{$Peak Weekday, Peak Weekend, Off Peak$\}$ in year $y \in \{2010, \ldots, 2018\}$. By construction shares of CRRs over the three firm types for a location pair at a specific ToU in a particular year sum to 100[26].

Several distinctive patterns across the firm types can be observed from Figure 4. Generating firms and retailers have a more localized portfolio than traders though certain changes are visible post 2014. We observe that generating firms own a much higher percentage of CRRs across specific location pairs like W–W, S–S, N–N, and H–H than any other pairs. Apart from a more diversified spatial portfolio post 2014 in case of generators, we also see a rise in their share of CRRs across locations with Source at West. On the other hand, we also notice a general decline in CRR share post 2014 for retailers which is also evident from summary statistics in Table 6.

Presence of localization as well as increase in share across West CRRs for generators can be attributed to the spatial aspect of electricity generation in Texas. Even though recent years have seen a rise in wind generation, natural gas and coal still dominate the share of electricity generation in Texas[27]. Interestingly, most natural gas and coal power plants are located in the South, North, and Houston zones of Texas whereas most wind farms are populated in the West. Concentration of different sources of electricity generation across specific regions makes a compelling case for why we observe generators to hold CRRs across those regions. However, gradual rise in wind generation aided by presence of transmission infrastructure due to CREZ could be a reason we observe generating firms diversifying their CRR portfolios in the West.

Location specificity is also observed for retailers and is almost similar across the three ToUs. The reason behind this pattern is akin to that of generating firms. Because North, South, and Houston are marked by higher share of residential and industrial customers of electricity, retailers have greater incentives to hold CRRs across these regions than across West. Traders on the other hand exhibit the most diversification in their spatial ownership of CRR. Lack of physical assets and electricity customers could provide traders with greater flexibility than other

26. For example, the sum of cells with the address $i \times j$ where i denotes the location-pair and j denotes the year for the heat-maps corresponding to Peak Weekday for Generator, Retailer, and Trader is 100.

27. The annual electricity generation from coal in Texas decreased from 39.8 percent in 2011 to 25.9 percent in 2018, whereas it increased for natural gas from 41.5 percent in 2011 to 45.4 percent in 2018. The share of wind on the other hand saw a rise from mere 7.7 percent in 2011 to about 17.6 percent in 2018 (EIA 2019).

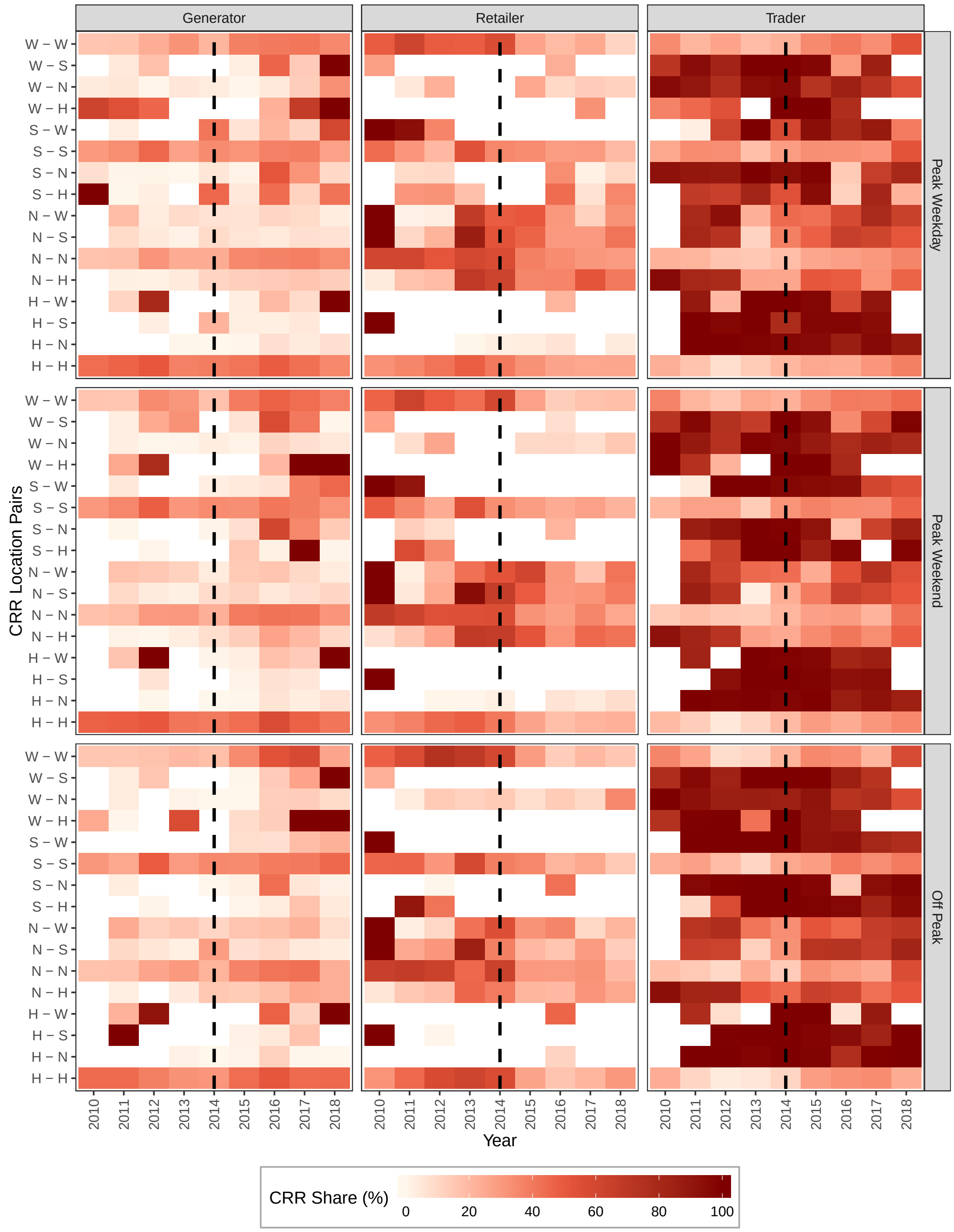


Figure 4: Heat-map depicting the percentage of CRRs held by various firm types at different location pairs annually from 2010 – 2018 across ToUs. Dashed vertical line marks transmission integration: 2014.

market players to have a more diversified portfolio and adopt a more speculative position in the market.

The idiosyncratic factors that drive firms to hold specific CRRs along with spatial heterogeneity of treatment as seen in Figure 3 lead us to observe the effects in Table 7. With an increase in ownership across West and a relatively non-flexible portfolio, generators show strongest negative effects followed by retailers who are mostly concentrated in non-West regions. Traders have a more distributed portfolio and are primarily aimed at speculation, exhibit the least effect of CREZ transmission expansion.

B. Changes in ownership across price distribution:
Using a similar strategy we explore the heterogeneity in the ownership of CRRs at different quintiles of price distribution. Each of the 9 smaller heat-maps in Figure 5 are 4×9 matrix with quintile groups as rows and years as columns. These cells measure the percentage share of CRRs given by:

$$\% \text{ of CRRs} = \frac{q^f_{\varphi,y,T}}{\sum_f q^f_{\varphi,y,T}} \times 100 \tag{4}$$

where, $q^f_{\varphi,y}$ is the quantity of CRRs (in MW) owned by firm type $f \in \{\text{Generator, Retailer, Trader}\}$ that fall in the quintile $\varphi \in \{1, 2, 3, 4\}$ at ToU $T \in \{\text{Peak Weekday, Peak Weekend, Off Peak}\}$ in year $y \in \{2010, \ldots, 2018\}$. The four quintiles are defined as the four equally sized intervals obtained using the three quantiles ($\tau = 0.25, 0.50,$ and 0.75) of CRR market clearing prices for each year. Similar to the heat-map in Figure 4, shares of CRRs over the three firm types for a quintile at a specific ToU in a particular year sum to 100[28].

As evident from Figure 5, there is a great deal of similarity in the patterns across ToUs, but not across different firm types. The heat-map shows that generators tend to hold a substantially larger share of CRRs with prices below the median than the CRRs at higher quintiles. This pattern is pronounced post 2014 wherein the share of CRRs at first and second quintiles is noticeably higher across the three ToUs. Retailers on the other hand show a substantial decrease in share of CRRs across all quintiles and a much more uniform pattern post 2014. Financial traders exhibit higher share of ownership of CRRs at upper quintiles post 2014

28. For example, the sum of cells with the address $i \times j$ where i denotes the quintile and j denotes the year for the heat-maps corresponding to Peak Weekday for Generator, Retailer, and Trader is 100.

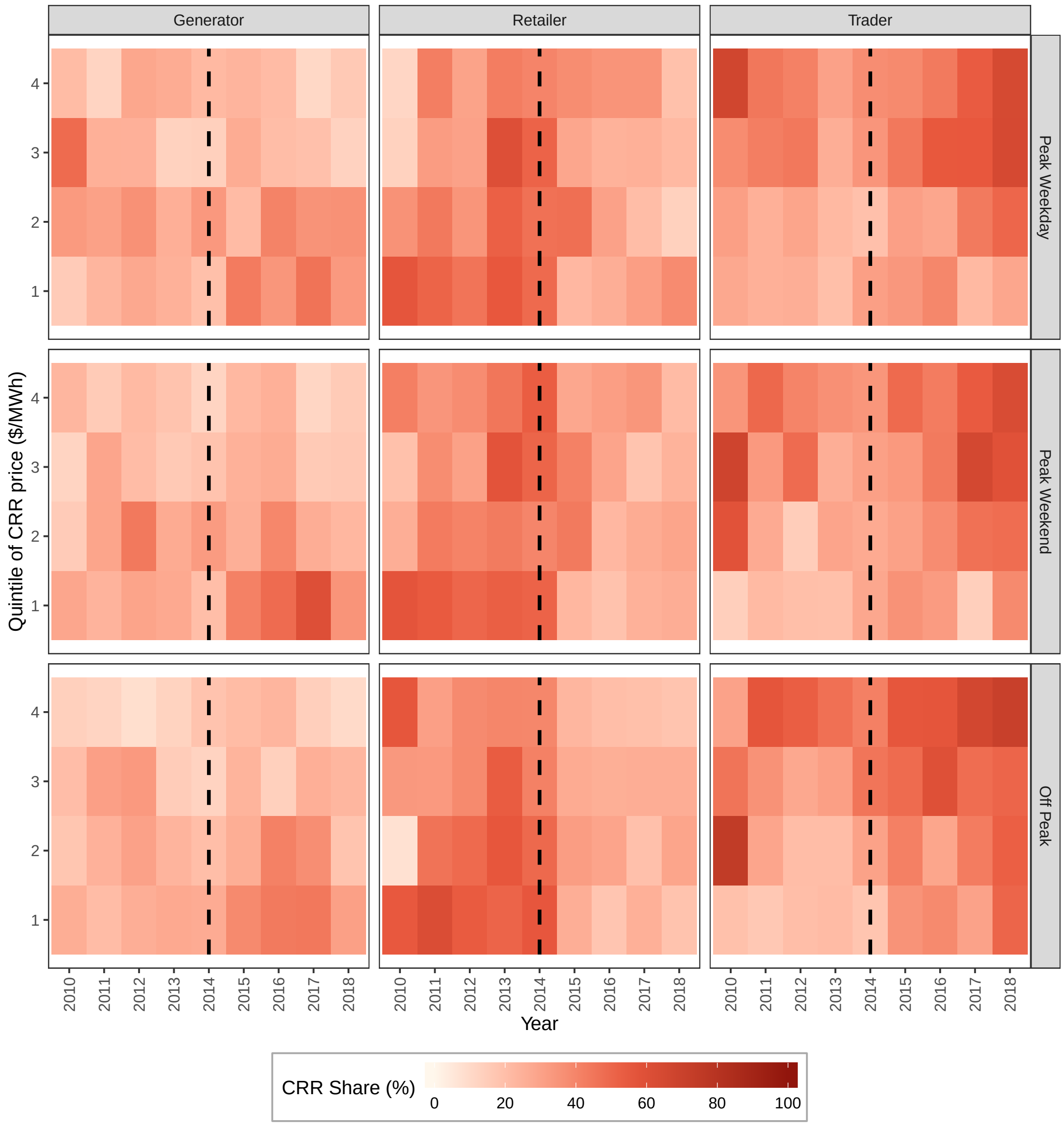


Figure 5: Heat-map depicting the percentage of CRRs held by various firm types at different price quantiles annually from 2010 – 2018 across ToUs. Dashed vertical line marks transmission integration: 2014.

across all ToUs. These patterns can be attributed to the incentives and strategies adopted by different firms in the market.

Due to their physical assets and presence of consumers on the retail side, generators and retailers have greater incentives to hedge future congestion risk than traders. Therefore, they tend to hold higher share of CRRs that have a lower probability of congestion, reflected as a lower market clearing price in their portfolio. Traders take a more speculative position in the market which provides them greater flexibility to hold contracts at different price points so as to maximize their profits. This strategy is evident from the changing patterns across the major firm types. The result of this flexibility is reflected in the estimates reported in Table 7 wherein we observe the effect of CREZ transmission to be higher for retailers and generators than traders. The results of firm heterogeneity across the ToUs are also consistent with the aggregate results reported in Table 2.

The above discussion sheds light to the fact that the heterogeneity observed across different market participants is due to the strategy employed by these firms in the market. Albeit there are numerous ways to measure and test these hypothesis, owing to data limitations we illustrate it in a simplified manner using heatmaps that are helpful in thinking about the reasons behind the results obtained from our statistical analysis. This evidence can be complemented with detailed bidding data of firms to explore related mechanisms and is an avenue for future research.

6 Convergence of prices post CREZ

Congestion in wholesale electricity markets due to transmission constraints could lead to significant welfare loss as high cost generators are dispatched before low cost ones. Transmission congestion is reflected as a price wedge between different regions and can be mitigated by transmission expansion between those regions (Joskow and Tirole 2005). The effect of transmission expansion on CRR prices is therefore informative about future congestion in the electricity market. Thus, convergence of CRR prices across different locations due to transmission expansion serves as a useful indicator of efficiency of the CRR market which in turn could be informative about the efficiency of the wholesale market.

Historically, West Zone of Texas was associated with high CRR prices owing to congestion due to lack of transmission capacity (Potomac Economics 2015). Therefore, we look whether there is evidence of convergence between prices of CRRs associated with West and the CRRs associated with Other zones. To motivate this discussion, we plot monthly average prices of CRRs linked with West zone and CRRs linked with other zones for the three ToUs in Figure 6. Clear pattern of convergence amongst these contracts is apparent for all ToUs. The convergence in prices is perhaps most significant for CRRs at Peak Weekend followed by Off

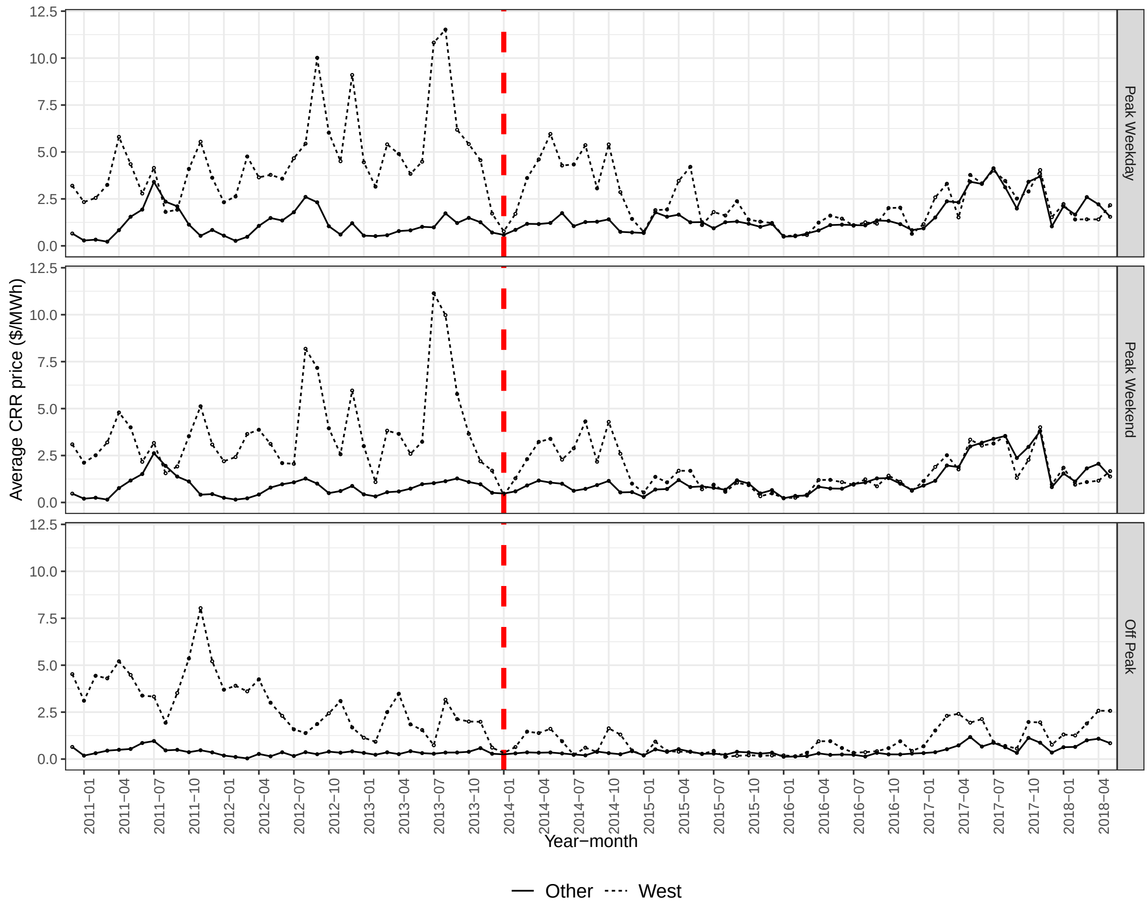


Figure 6: Convergence of average market clearing prices($/MWh) between CRRs with West Source/Sink and Other Source and/or Sink post CREZ transmission integration. Dashed vertical line marks CREZ completion: January 2014.

Peak and Peak Weekday[29].

In order to formally test for the convergence we employ an empirical strategy that is similar in spirit to that of Borenstein et al. (2008). Although, in their paper, Borenstein et al. (2008) test for convergence between forward and spot prices in the CAISO market, we estimate a slightly different specification to fit our context:

$$\left[\mathrm{CRR}_t^{\tau,\mathrm{West}} - \mathrm{CRR}_t^{\tau,\mathrm{other}}\right] = \alpha_1 \cdot \mathbb{1}\{t < 01-2014\} + \alpha_2 \cdot \mathbb{1}\{t \geq 01-2014\} + \epsilon_t \quad (5)$$

The dependent variable in Equation 5 is the difference between clearing price of

29. We present a similar graph on spatial convergence of prices for the three firm types. Although the extent of convergence is difference across firms, the results are qualitatively similar across the ToUs. The graph is included in the Appendix, but we restrict our focus to aggregate results.

CRR with Source and/or Sink at West ($\mathrm{CRR}_t^{\mathrm{West}}$) and CRR with Source and Sink at other zones ($\mathrm{CRR}_t^{\mathrm{other}}$). Since the number of contracts in these two groups differ in each period, we instead use different statistics (τ) of prices. Specifically, we use difference of average, 25th, 50th, and 75th quantile of the two terms as dependent variable. Thus, the total number of observations in each regression is 90. The parameters of interest are the two binary variables that capture the average convergence of prices for the period prior and post transmission integration. $\hat{\alpha}_1 > \hat{\alpha}_2$ implies that the difference in prices of contracts across the two sets of locations was lower post transmission integration and is therefore indicative of spatial convergence.

The results of this estimation are reported in the form of bar plots with 95 percent confidence intervals in Figure 7. A general pattern evident from Figure 7 is that of a decrease in the difference of various statistics of prices post transmission integration across the two classes of CRR for all the three ToUs. The convergence in average prices is highest for CRRs at Peak Weekend followed by CRRs at Off Peak and Peak Weekday. The statistical evidence presented in Figure 7 corroborates the pattern observed in Figure 6 for average CRR prices for the three ToUs.

The pattern across the three ToUs for various statistics τ is quite uniform. We see a dramatic drop in the estimate of α_2 across all the statistics of the dependent variable. Convergence in prices is strongest between Peak Weekend CRRs where $\hat{\alpha}_2$ is statistically indistinguishable from zero at 5 percent critical level for average, 50th, and 75th quantile. These results point to a gain in efficiency of the CRR market post transmission integration in terms of significant convergence in prices between the CRRs across West and CRRs across other zones.

This evidence of convergence in prices of CRRs between different locations could lower incentives for speculative behavior amongst market players. This would in turn lower opportunities for profits from CRR payouts due to a drop in expected congestion(Bushnell, Harvey, and Hobbs 2018). As discussed before, these results indicate an increase in efficiency of the wholesale market as well. We complement the findings of LaRiviere and Lu (2017), who find evidence of a drop in transmission congestion loss due to convergence in wholesale electricity prices as a result of CREZ based transmission expansion.

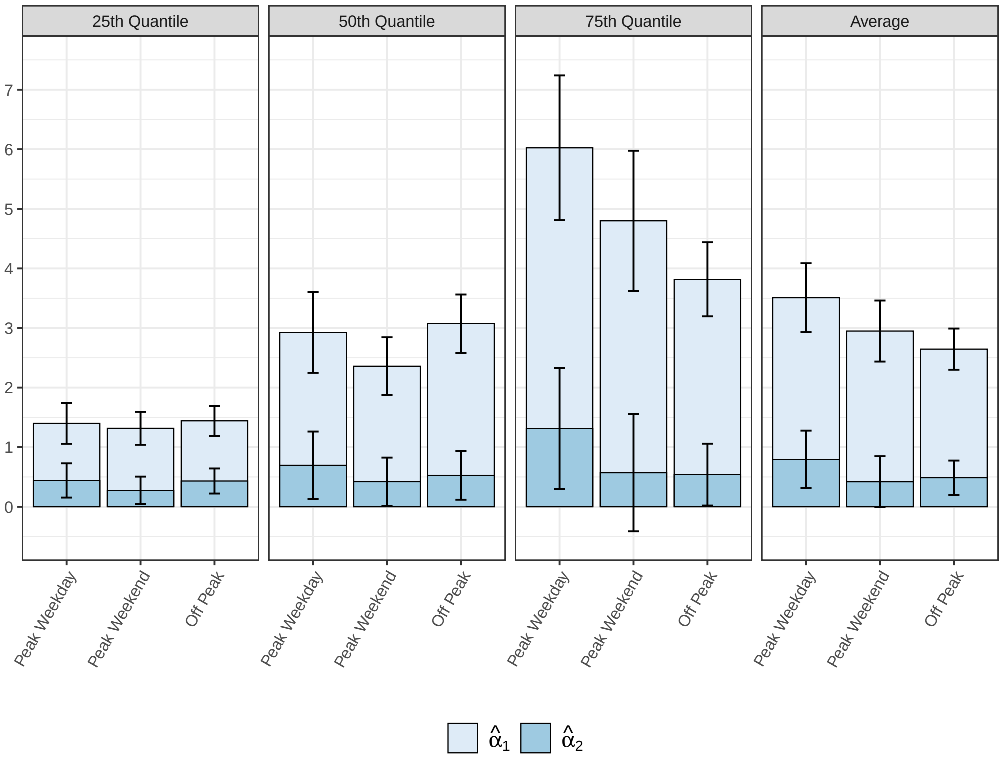


Figure 7: Estimates of $\hat{\alpha}_1$ and $\hat{\alpha}_2$ in Equation 5 with each panel representing the result for each statistic (τ) of the dependent variable $\text{CRR}_t^{\tau,\text{West}} - \text{CRR}_t^{\tau,\text{Other}}$.

7 Change in auction expenditure post CREZ

The empirical analysis suggests that CREZ transmission integration led to a significant decline in prices for Peak Weekday, Peak Weekend, and Off Peak with considerable spatial and distributional heterogeneity. A relevant policy question is the extent to which these estimates translate to a decrease in auction expenditure by firms. Combining the per-hour estimates with information on total time of use hours for Peak Weekday, Peak Weekend, and Off Peak for all the months post transmission shock, we compute aggregate estimates of change in expenditure. Recall that the market clearing prices of CRR contracts is determined via uniform price auction conducted by ERCOT. Lowering of prices due to an exogenous change in transmission would be reflected as a decrease in auction expenditure which could be informative about the change in expectations that market participants form for future congestion in response to change in transmission.

Alluding to the treatment effects literature, the conditional average treatment effect on the CRR price for a contract between i, j at period t as a result of transmission shock (T=1) conditional on a set of control variables $(\mathbf{X}_{ij,t})$ can be written as:

$$\begin{aligned} \Delta\mathrm{CRR}_{ij,t} &= E[\mathrm{CRR}_{ij,t}|\mathrm{T}=1, \mathbf{X}_{ij,t}] - E[\mathrm{CRR}_{ij,t}|\mathrm{T}=0, \mathbf{X}_{ij,t}] \\ &= \hat{\beta}_1 + \hat{\beta}_2 \cdot trend \end{aligned} \tag{6}$$

Change in expenditure, $\Delta\mathrm{E}_{ij,t}$ (\$/h) can then be expressed as:

$$\Delta\mathrm{E}_{ij,t} = \Delta\mathrm{CRR}_{ij,t} \times q_{ij,t} = (\hat{\beta}_1 + \hat{\beta}_2 \cdot trend) \times q_{ij,t}$$

Multiplying the quantity of contracts $q_{ij,t}$ with the total ToU hours for period t, converts these numbers in dollar terms:

$$\Delta\mathrm{E}(\$) = \left[\left(\hat{\beta}_1 \cdot \sum_{t \geq 01-2014} \sum_{i,j} (q_{ij,t} \cdot \mathrm{ToU}_t)\right) + \left(\hat{\beta}_2 \cdot \sum_{t \geq 01-2014} \sum_{i,j} \big(trend \cdot q_{ij,t} \cdot \mathrm{ToU}_t\big)\right)\right] \tag{7}$$

where, ToU_t is the number of ToU hours for Peak Weekday, Peak Weekend, or Off Peak at period t[30]. Using the estimates of baseline specification from Table 2 in Equation 7, we derive the total change in expenditure. The result of this exercise is summarized in Table 8.

Because Peak Weekday has the maximum number of ToU hours, we observe the drop in expenditure to be highest for Peak Weekday CRRs, approximately \$240.6 million which is about 3.54 percent of the total cost of CREZ (\$6.8 billion). This is followed by contracts at Peak Weekend, wherein the decrease in expenditure is approximately \$81.7 million ($\sim$ 1.20 percent of total cost of CREZ). In case of Off Peak, we observe an increase in expenditure as opposed to a decline. This is because we estimate a positive trend effect that is about \$0.038/MWh per month in our baseline results. This effect offsets the negative effect of treatment effect in case of Off Peak. Hence, the total decrease in expenditure is approximately \$261.1 million ($\sim$ 3.84 percent of total cost of CREZ) over the period January 2014 – May 2018. These cost estimates are pretty substantial in magnitude and reflect how closely transmission is linked to the CRR market specifically the prices. The magnitude of these estimates provides alternative interpretation of the impact of transmission on expected congestion at DAM, as indicated by decline in prices and therefore a subsequent drop in auction expenditure by firms.

30. Data on ToU hours for the sample is compiled from ERCOT.

Table 8: Aggregate change in auction expenditure

Time of Use	$\Delta E(\$)$	$\left[\frac{\Delta E}{\text{Cost of CREZ}}\right]$
	(1)	(2)
Peak Weekday	−240,599,008	−3.54%
Peak Weekend	−81,687,284	−1.20%
Off Peak	61,138,737	0.90%
Total	−261,147,555	−3.84%

Notes:
Column (1) is the total change in expenditure ($\Delta E(\$)$) calculated using estimates from Table 2 in Equation 7. Column(2) expresses the change in total expenditure as a percentage of cost of CREZ ($6.8 billion). All estimates are for the period January 2014 – May 2018.

8 Conclusions

Transmission infrastructure has wide ranging impacts on various aspects of an electricity market, however, the empirical literature exploring the effect of transmission expansion on Congestion Revenue Rights (CRR) has been limited. CRR prices reveal information about the expectation market players place on future transmission congestion in the electricity market. Studying this issue is of importance given the increasing necessity to expand transmission infrastructure in order to accommodate various renewable energy resources. Using the case of CREZ from the Texas electricity market, this paper presents a detailed analysis of how a geographical change in electricity transmission line network affects CRR prices.

CREZ transmission project significantly expanded the electricity transmission network in the West Zone to relive the transmission congestion between West and other zones of the market. This paper finds evidence that CREZ based transmission expansion led to a significant lowering of CRR prices across both Peak and Off Peak hours. This decline in prices is largest in magnitude for CRRs associated with the West Zone along with a negative trend post expansion for peak hours on weekdays and weekends. These results provide evidence that CREZ led to a significant decline in the market players' expectation of transmission congestion between West and other zones. This is reflected as a convergence in prices between West and other zones and is indicative of an increase in efficiency of the CRR market in terms of less speculative behavior for profits and perhaps a decline in financial losses due to transmission congestion at the Day Ahead Market.

We also find substantial heterogeneity in the effect of transmission expansion across different firm types. Generating firms exhibit a larger decline in the prices of CRRs followed by retailers and traders. As we argue, the pattern of decline observed from the results is tied to the physical interests and incentives that various market players have in the market. For example, generating firms show less flexibility than financial traders in terms of their choice of location pair of CRRs. Traders own a more diverse portfolio of CRRs with a higher share of contracts across different zones than generators. These differences in the ownership pattern across different groups of market participants allow us to observe the heterogeneity across these market participants.

Several years since CREZ, congestion continues to increase across different zones in the Texas electricity market (Potomac Economics 2019). Recognizing this, ERCOT has been investing in transmission lines across the state[31]. Our findings shed light on how these investments in transmission capacity would affect the CRR market as well as the strategic behavior of different market participants. Another cause of concern is the over investment in wind projects in response to additional transmission due to CREZ. While this increases the electricity generated through wind and the subsequent 'greening of the grid', it has also led to higher wind curtailment and increase in transmission congestion (Potomac Economics 2019). Thus studying the production decision of generating firms and the location choice of wind farms in response to transmission expansion is a potential area for future research.

31. For example, ERCOT has endorsed over $600 million worth of transmission expansion projects across West Texas as well as several projects in Houston and South Zones (ERCOT 2018a).

References

Adamson, Seabron, Thomas Noe, and Geoffrey Parker. 2010. Efficiency of financial transmission rights markets in centrally coordinated periodic auctions. *Energy Economics* 32 (4): 771–778.

Barreca, Alan I, Jason M Lindo, and Glen R Waddell. 2016. Heaping-induced bias in regression-discontinuity designs. *Economic Inquiry* 54 (1): 268–293.

Bills, Jeff. 2017. *The Texas Competitive Renewable Energy Zone Process.* Electric Reliability Council of Texas.

Birge, John R, Ali Hortaçsu, Ignacia Mercadal, and J Michael Pavlin. 2018. Limits to Arbitrage in Electricity Markets: A case study of MISO. *Energy Economics* 75:518–533.

Borenstein, Severin. 2000. Understanding competitive pricing and market power in wholesale electricity markets. *The Electricity Journal* 13 (6): 49–57.

Borenstein, Severin, and James Bushnell. 2015. The US electricity industry after 20 years of restructuring. *Annual Review of Economics* 7 (1): 437–463.

Borenstein, Severin, James B Bushnell, and Frank A Wolak. 2002. Measuring market inefficiencies in California's restructured wholesale electricity market. *American Economic Review* 92 (5): 1376–1405.

Borenstein, Severin, James Bushnell, Christopher R Knittel, and Catherine Wolfram. 2008. Inefficiencies and market power in financial arbitrage: a study of California's electricity markets. *The Journal of Industrial Economics* 56 (2): 347–378.

Borenstein, Severin, James Bushnell, and Steven Stoft. 2000. The competitive effects of transmission capacity in a deregulated electricity industry. *RAND Journal of Economics* 31 (2): 294–325.

Bushnell, James. 1999. Transmission rights and market power. *The Electricity Journal* 12 (8): 77–85.

Bushnell, James, Scott M Harvey, and Benjamin F Hobbs. 2018. Opinion on Congestion Revenue Rights Auction Efficiency. Discussion Paper, Market Surveillance Committee of the California ISO.

CAISO. 2016. Shortcomings in the Congestion Revenue Right auction design. Discussion Paper, CAISO Department of Market Monitoring.

Cardell, Judith B, Carrie Cullen Hitt, and William W Hogan. 1997. Market power and strategic interaction in electricity networks. *Resource and energy economics* 19 (1-2): 109–137.

Chimeli, Ariaster B, and Rodrigo R Soares. 2017. The use of violence in illegal markets: Evidence from Mahogany trade in the Brazilian Amazon. *American Economic Journal: Applied Economics* 9 (4): 30–57.

Chokshi, Niraj, and Maggie Astor. 2017. Hurricane Harvey: The Devastation and What Comes Next. Retrieved from: `https://www.nytimes.com/2017/08/28/us/hurricane-harvey-texas.html`, *New York Times.*

Davis, Lucas, and Catherine Hausman. 2016. Market impacts of a nuclear power plant closure. *American Economic Journal: Applied Economics* 8 (2): 92–122.

Deng, Shi-Jie, Shmuel Oren, and AP Meliopoulos. 2010. The inherent inefficiency of simultaneously feasible financial transmission rights auctions. *Energy Economics* 32 (4): 779–785.

Du, Xiaodong, and Ofir D Rubin. 2018. Transition and integration of the ERCOT market with the Competitive Renewable Energy Zones Project. *The Energy Journal* 39 (4).

EIA. 2019. *Electricity Data Browser, EIA.* Data retrieved from: `https://www.eia.gov/electricity/data/browser/`. US Energy Information Administration.

ERCOT. 2008. *Competitive Renewable Energy Zones (CREZ) Transmission Optimization Study.* Technical report. Electric Reliability Council of Texas.

———. 2015. *ERCOT Nodal Market: Congestion Revenue Rights System Market Participant Handbook.* Version 3.3. December.

———. 2018a. *2017 State of the Grid.* April.

———. 2018b. *ERCOT Nodal Protocols.* Section 7: Congestion Revenue Rights.

———. 2018c. *ERCOT Nodal Protocols.* Section 4: Day-Ahead Operations.

———. 2018d. *Glossary.* Electric Reliability Council of Texas. Retrieved from: `http://www.ercot.com/glossary/`.

———. 2020. Fact Sheet 2019. Electric Reliability Council of Texas. Retrieved from: `http://www.ercot.com/content/wcm/lists/197391/ERCOT_Fact_Sheet_2.5.20.pdf`.

Hogan, William W. 1992. Contract networks for electric power transmission. *Journal of Regulatory Economics* 4 (3): 211–242.

Ito, Koichiro, and Mar Reguant. 2016. Sequential markets, market power, and arbitrage. *American Economic Review* 106 (7): 1921–57.

Joskow, Paul L, and Jean Tirole. 2000. Transmission rights and market power on electric power networks. *The Rand Journal of Economics:* 450–487.

———. 2005. Merchant Transmission Investment. *The Journal of Industrial Economics* 53 (2): 233–264.

LaRiviere, Jacob, and Xueying Lu. 2017. Transmission constraints, intermittent renewables and welfare. Working Paper.

Lasher, Warren. 2014. The Competitive Renewable Energy Zones Process. In *Quadrennial energy review public meeting: state, local and tribal issues.* US Department of Energy, Santa Fe, NM.

Leslie, Gordon. 2018. Who benefits from ratepayer-funded auctions of transmission congestion contracts? Evidence from New York. Working Paper.

Mount, Timothy D, and Jaeuk Ju. 2014. An econometric framework for evaluating the efficiency of a market for transmission congestion contracts. *Energy Economics* 46:176–185.

New York Times. 2016. Making Way for Wind Power. Editorial. Retrieved from: `https://www.nytimes.com/2016/04/05/opinion/making-way-for-wind-power.html`.

Potomac Economics. 2015. *2014 State of the Market Report for the ERCOT Electricity Markets.* May.

———. 2019. *2018 State of the Market Report for the ERCOT Electricity Markets.* June.

Ryan, Nicholas. 2017. *The competitive effects of transmission infrastructure in the Indian electricity market.* National Bureau of Economic Research (NBER) Working Paper 23106.

Wolak, Frank A. 2015. Measuring the competitiveness benefits of a transmission investment policy: The case of the Alberta electricity market. *Energy policy* 85:426–444.

A Appendix

A.1 Acronyms

CREZ Competitive Renewable Energy Zones.

CRR Congestion Revenue Right.

DAM Day Ahead Market.

ERCOT Electric Reliability Council of Texas.

GW Gigawatt.

ISO Independent System Operator.

LMP Locational Marginal Price.

MIS Market Information System.

MW Megawatt.

MWh Megawatt-hours.

PUCT Public Utility Commission of Texas.

ToU Time of Use.

A.2 Classification of CRR account holders into firm types

Each account holder that appears in the data set and owns a CRR has been classified into three firm types: Generator, Retailer, and Trader. This categorization follows closely to the one used in Leslie (2018). We define Retailer as any firm that purchases wholesale electricity and provides electricity to residential and/or corporate consumers. Firms that own generation assets and participate in trading CRRs in Texas electricity market are classified as Generators. Finally, firms that neither have any physical (generation) assets nor serve residential and/or corporate consumers, but only participate in CRR trading are classified as Traders. Different firms or more broadly firm types might have different motives in the market, some might be interested in hedging their risks whereas some might have speculative interests and make profit. The classification is based on our judgement using information presented in the firm's website, company overview at www.bloomberg.com and account holder listing at ERCOT.

Generator: BJ Energy LLC; Brazos Electric Power Co Op Inc.; Calpine Power Management LLC; Cargill Power Markets LLC; City Of Georgetown; EDF Energy Services LLC; Exelon Generation Company LLC; Franklin Power LLC; Frontier Utilities LLC; Longhorn Energy LP; DBA Longhorn Electricity Marketing LP; Lower Colorado River Authority; MAG Energy Solutions Inc.; Midamerican Energy Company; NRG Texas Power LLC; NRG Texas Power LLC (GME); Optim Energy Marketing LLC; Pepco Energy Services Inc.; Shell Energy North America (US) LP; Source Operations Group LLC; Westar Energy Inc.

Retailer: BP Energy Company; Champion Energy Marketing LLC; Cirro Group INC; City Of Georgetown; Consolidated Edison Solutions INC; Denton Municipal Electric; EDF Energy Services LLC; First Choice Power LP; Frontier Utilities LLC; GDF Suez Energy Resources Na Inc.; Gexa Energy LP; Green Mountain Energy Company; Luminant Energy Company LLC REPS; Midamerican Energy Services LLC; New Braunfels Utilities; Noble Americas Energy Solutions LLC; Noble Americas Gas And Power Corp; Northern States Power Company; Spark Energy LP; Talen Energy Marketing LLC; Texas Energy Transfer Power Llc; Texas Power LP; Trieagle Energy LP; Yuma Electric LLC.

Trader: Appian Way Energy Partners Southcentral LP; Arcturus Power Trading LLC; Aspire Capital Management LLC; ATNV Energy LP; Barton Fund LLC; Biourja Power LLC; Boston Energy Trading And Marketing LLC; Citigroup Energy Inc.; Constellation Energy Commodities Group Inc.; Darby Energy LLLP; DB Energy Trading LLC; DC Energy Texas LLC; Denver Energy LLC DBA Denen LLC; Direct Energy LP; DTE Energy Trading Inc.; Dyon LLC; EDF Trading North America LLC; Edison Mission Marketing And Trading Inc.; Endure Energy LLC; Engelhart CTP (US) LLC; Inertia Power III LP; J Aron And Company LLC; JP Morgan Ventures Energy Corporation; Keystone Energy Partners LP; Louis Dreyfus Energy Services LP; Luminant Energy Company LLC Trading; Macquarie Energy LLC; Merrill Lynch Commodities Inc.; Met Texas Trading LP; Met Texas Virtual LP; Midwest Energy Trading East LLC; Monterey TX LLC; Monterey TXF LLC; Morgan Stanley Capital Group Inc.; Nextera Energy Power Marketing LLC; North Maple Energy LLC; NPM Energy Llc; NRG Power Marketing LLC; Pacific Summit Energy LLC; Polaris Power Trading LLC; Raiden Commodities LP; Rainbow Energy Marketing Corporation; Rigby Energy Resources LP; PMH Energy LP; Sandalwood Power LLC; Saracen Energy West LP; SESCO Southwest Trading LLC; SESCO Southwest Trading LLC CAISO; SESCO Southwest Trading LLC KP; Shell Energy North America (US) LP; SIG Energy LLLP; Sunico LLC; SW Power Trading LLC; Trailstone Power LLC; Twin Eagle Resource Management LLC; TX Active Power Investments LLC; UNCIA Energy LP Series E; Uniper Global Commodities North America LLC; VBE Investments LLC; Vitol Inc; West Oaks Energy LP; Wolverine Trading LLC; XO Energy TX2 LP.

A.3 Additional Tables

Table A.1: Robustness check results for baseline regression for Peak Weekday, Peak Weekend, and Off Peak CRR

Peak Weekday	(1)	(2)	(3)	(4)
$D_{t\geq 01-2014}$	-0.769^{***}	-0.673^{***}	-0.983^{***}	-0.915^{***}
	(0.235)	(0.228)	(0.300)	(0.300)
$D_{t\geq 01-2014} \times trend$	0.002	0.003	-0.010	-0.016
	(0.006)	(0.006)	(0.012)	(0.012)
Observations	3367	3367	3367	3367
Source and Sink FE		×	×	×
Time trend and Month FE			×	×
Month × Source/Sink FE				×
FE for 2017	×	×	×	×
Peak Weekend	(5)	(6)	(7)	(8)
$D_{t\geq 01-2014}$	-0.825^{***}	-0.885^{***}	-1.050^{***}	-1.049^{***}
	(0.199)	(0.197)	(0.296)	(0.286)
$D_{t\geq 01-2014} \times trend$	0.008	0.011	0.002	-0.002
	(0.005)	(0.005)	(0.011)	(0.011)
Observations	3266	3266	3266	3266
Source and Sink FE		×	×	×
Time trend and Month FE			×	×
Month × Source/Sink FE				×
FE for 2017	×	×	×	×
Off Peak	(9)	(10)	(11)	(12)
$D_{t\geq 01-2014}$	-0.929^{***}	-0.883^{***}	-0.338^{***}	-0.326^{***}
	(0.125)	(0.125)	(0.115)	(0.116)
$D_{t\geq 01-2014} \times trend$	0.010^{***}	0.012^{***}	0.039^{***}	0.038^{***}
	(0.004)	(0.004)	(0.007)	(0.006)
Observations	3268	3268	3268	3268
Source and Sink FE		×	×	×
Time trend and Month FE			×	×
Month × Source/Sink FE				×
FE for 2017	×	×	×	×

Notes:
The dependent variable is CRR market clearing price for all the three samples. The variable of interest $D_{t\geq 01-2014}$ is an indicator variable marking the completion of CREZ in January 2014. Robust standard errors, clustered at year-month level are presented in parenthesis. Significance: *p<0.1; **p<0.05; ***p<0.01

Table A.2: Robustness check results for distributional heterogeneity in the effect of transmission integration for Peak Weekday

	Quintile window (# months prior to Dec 2013)			
Peak Weekday	Base Model	6 Months	12 Months	18 Months
	(1)	(2)	(3)	(4)
$D_{t\geq 01-2014}$ × Quintile 1	-0.415^{*}	-0.382	-0.382	-0.451^{*}
	(0.240)	(0.235)	(0.235)	(0.246)
$D_{t\geq 01-2014}$ × Quintile 2	-0.176	-0.236	-0.236	-0.314
	(0.274)	(0.288)	(0.288)	(0.295)
$D_{t\geq 01-2014}$ × Quintile 3	-1.218^{***}	-1.215^{***}	-1.215^{***}	-1.341^{***}
	(0.350)	(0.352)	(0.352)	(0.511)
$D_{t\geq 01-2014}$ × Quintile 4	-2.561^{***}	-2.600^{***}	-2.600^{***}	-2.132^{***}
	(0.919)	(0.917)	(0.917)	(0.555)
Observations	3367	3367	3367	3367
R^2	0.441	0.440	0.440	0.419

Notes:

The dependent variable is CRR market clearing price at Peak Weekday for all the three samples. $D_{t\geq 01-2014}$ is an indicator variable marking the completion of CREZ in January 2014. Different specifications use different windows to take the average of CRR price for quintile assignment. 'Base Model' uses December 2010 – December 2013, '6 Months' uses December 2010 – June 2013, '12 Months' uses December 2010 – December 2012, and '18 Months' uses December 2010 – June 2012. All specifications control for time trend t, source fixed effects (η_i), sink fixed effects (η_j), seasonality, and fixed effect for the year 2017. Robust standard errors, clustered at year-month level are presented in parenthesis. Significance: *p<0.1; **p<0.05; ***p<0.01

Table A.3: Robustness check results for distributional heterogeneity in the effect of transmission integration for Peak Weekend

Peak Weekend	Quintile window (# months prior to Dec 2013)			
	Base Model	6 months	12 months	18 months
	(1)	(2)	(3)	(4)
$D_{t\geq 01-2014}$ × Quintile 1	-0.441^{*}	-0.443^{*}	-0.443^{*}	-0.470^{*}
	(0.243)	(0.245)	(0.245)	(0.250)
$D_{t\geq 01-2014}$ × Quintile 2	-0.462^{*}	-0.423^{*}	-0.423^{*}	-0.465^{*}
	(0.242)	(0.246)	(0.246)	(0.254)
$D_{t\geq 01-2014}$ × Quintile 3	-1.292^{***}	-1.323^{***}	-1.323^{***}	-1.397^{***}
	(0.302)	(0.312)	(0.312)	(0.436)
$D_{t\geq 01-2014}$ × Quintile 4	-2.954^{***}	-2.294^{***}	-2.294^{***}	-2.267^{***}
	(0.901)	(0.744)	(0.744)	(0.543)
Observations	3266	3266	3266	3266
R^2	0.438	0.442	0.442	0.420

Notes:

The dependent variable is CRR market clearing price at Peak Weekend for all the three samples. $D_{t\geq 01-2014}$ is an indicator variable marking the completion of CREZ in January 2014. Different specifications use different windows to take the average of CRR price for quintile assignment. 'Base Model' uses December 2010 – December 2013, '6 Months' uses December 2010 – June 2013, '12 Months' uses December 2010 – December 2012, and '18 Months' uses December 2010 – June 2012. All specifications control for time trend t, source fixed effects (η_i), sink fixed effects (η_j), seasonality, and fixed effect for the year 2017. Robust standard errors, clustered at year-month level are presented in parenthesis. Significance: *p<0.1; **p<0.05; ***p<0.01

Table A.4: Robustness check results for distributional heterogeneity in the effect of transmission integration for Off Peak

	Quintile window (# months prior to Dec 2013)			
Off Peak	Base Model	6 months	12 months	18 months
	(1)	(2)	(3)	(4)
$D_{t\geq 01-2014} \times$ Quintile 1	0.532^{***}	0.487^{***}	0.469^{***}	0.623^{***}
	(0.156)	(0.148)	(0.139)	(0.135)
$D_{t\geq 01-2014} \times$ Quintile 2	0.385^{***}	0.327^{**}	0.579^{***}	0.268
	(0.142)	(0.136)	(0.175)	(0.190)
$D_{t\geq 01-2014} \times$ Quintile 3	0.102	-0.462^{**}	-0.387^{*}	0.173
	(0.227)	(0.184)	(0.201)	(0.222)
$D_{t\geq 01-2014} \times$ Quintile 4	-3.337^{***}	-3.725^{***}	-3.164^{***}	-3.262^{***}
	(0.466)	(0.467)	(0.508)	(0.468)
Observations	3268	3268	3268	3268
R^2	0.504	0.486	0.456	0.494

Notes:

The dependent variable is CRR market clearing price at Off Peak for all the three samples. $D_{t\geq 01-2014}$ is an indicator variable marking the completion of CREZ in January 2014. Different specifications use different windows to take the average of CRR price for quintile assignment. 'Base Model' uses December 2010 – December 2013, '6 Months' uses December 2010 – June 2013, '12 Months' uses December 2010 – December 2012, and '18 Months' uses December 2010 – June 2012. All specifications control for time trend t, source fixed effects (η_i), sink fixed effects (η_j), seasonality, and fixed effect for the year 2017. Robust standard errors, clustered at year-month level are presented in parenthesis. Significance: *p<0.1; **p<0.05; ***p<0.01

Table A.5: Convergence of market clearing price post CREZ transmission integration

Panel	Statistic	Parameter	$\text{CRR}_t^{\text{West}}$ - $\text{CRR}_t^{\text{other}}$		
			Peak Weekday	Peak Weekend	Off Peak
			(1)	(2)	(3)
A	Mean	$\hat{\alpha}_1$	3.507***	2.949***	2.646***
			(0.295)	(0.261)	(0.176)
		$\hat{\alpha}_2$	0.794***	0.419*	0.487***
			(0.247)	(0.218)	(0.147)
B	25th Quantile	$\hat{\alpha}_1$	1.400***	1.317***	1.442***
			(0.175)	(0.141)	(0.128)
		$\hat{\alpha}_2$	0.441***	0.275**	0.432***
			(0.146)	(0.118)	(0.107)
C	Median	$\hat{\alpha}_1$	2.926***	2.359***	3.073***
			(0.345)	(0.247)	(0.250)
		$\hat{\alpha}_2$	0.696**	0.420**	0.527**
			(0.289)	(0.207)	(0.209)
D	75th Quantile	$\hat{\alpha}_1$	6.024***	4.799***	3.817***
			(0.620)	(0.601)	(0.317)
		$\hat{\alpha}_2$	1.315**	0.570	0.539**
			(0.518)	(0.502)	(0.265)

Notes:
The dependent variable is the difference between market clearing price of CRRs with West Source and/or Sink and CRRs with Other Source and/or Sink ($\text{CRR}_t^{\text{West}}$ - $\text{CRR}_t^{\text{other}}$) at the three ToUs. Different panels present regression results of various statistics of the dependent variable at each period on the two binary variables $\mathbb{1}\{t < 01-2014\}$ and $\mathbb{1}\{t \geq 01-2014\}$ in Equation 5. Hence, each specification has 90 observations. Significance: *p<0.1; **p<0.05; ***p<0.01

A.4 Additional Figures

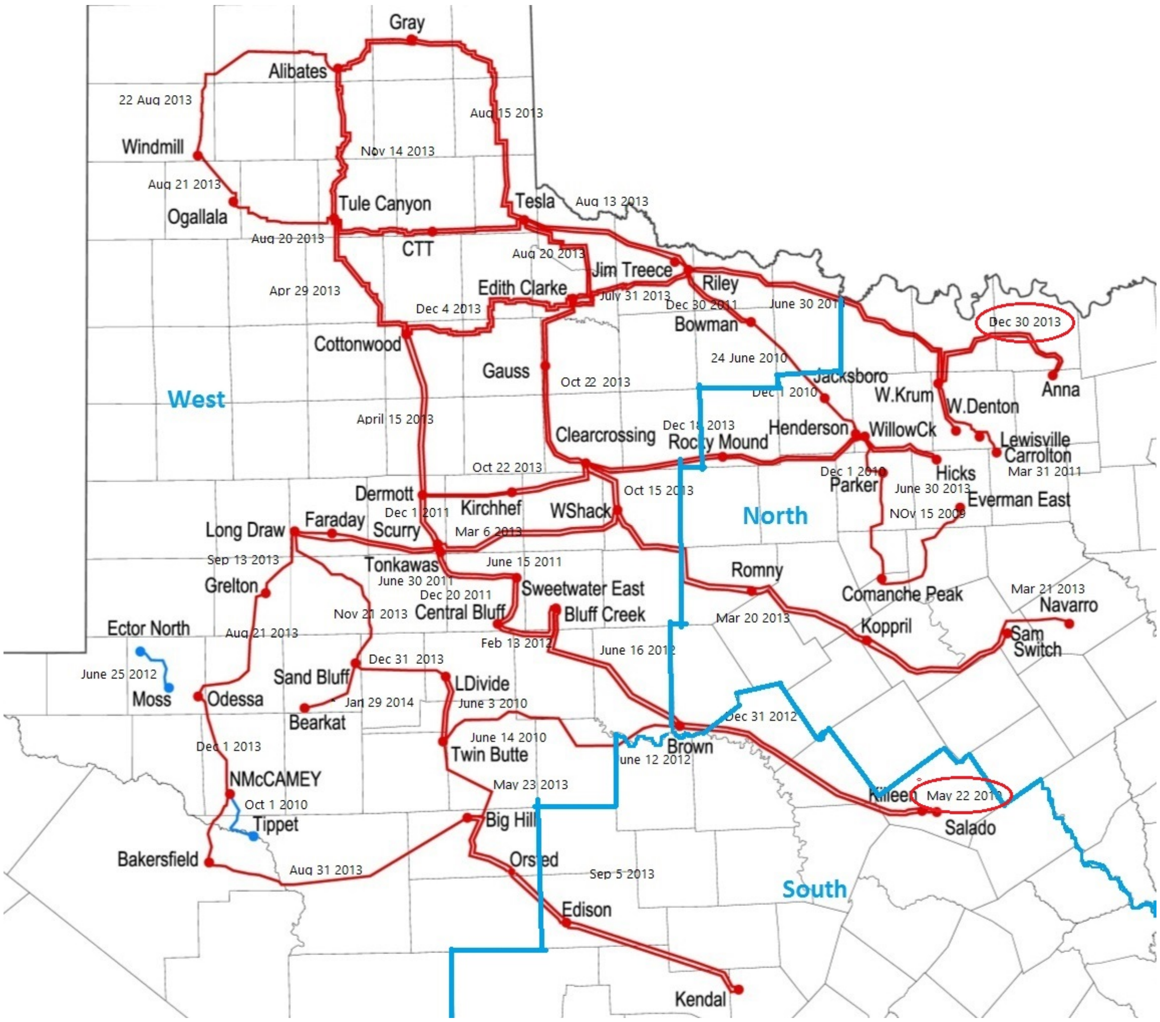
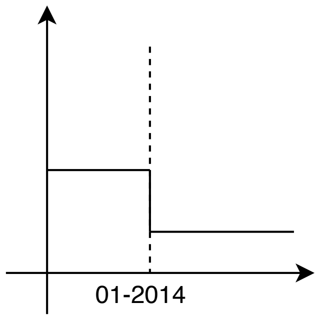
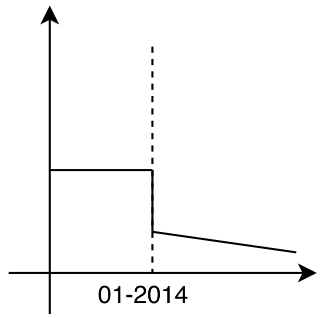


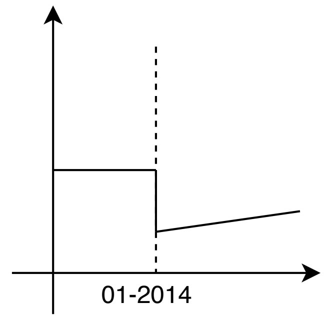
Figure A.1: Timeline and spatial location of new transmission lines constructed as part of CREZ. Red solid lines represent 345kV transmission lines. The entire network was planned to be completed and commissioned to be in service by December 31, 2013. Source: Du and Rubin (2018).



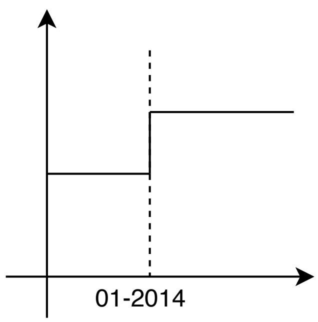
(a) $\hat{\beta}_1 < 0, \hat{\beta}_2 = 0$



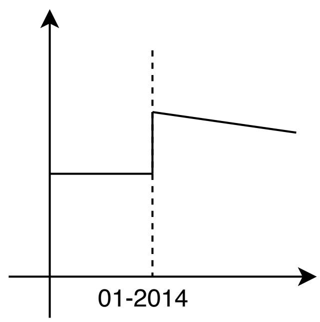
(b) $\hat{\beta}_1 < 0, \hat{\beta}_2 < 0$



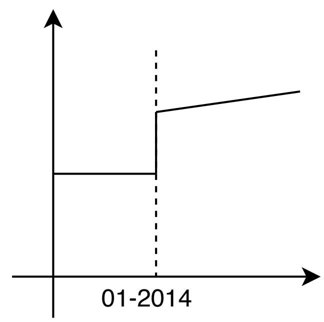
(c) $\hat{\beta}_1 < 0, \hat{\beta}_2 > 0$



(d) $\hat{\beta}_1 > 0, \hat{\beta}_2 = 0$



(e) $\hat{\beta}_1 > 0, \hat{\beta}_2 < 0$



(f) $\hat{\beta}_1 > 0, \hat{\beta}_2 > 0$

Figure A.2: Graphical interpretation of different cases of estimated coefficients $\hat{\beta}_1$ and $\hat{\beta}_2$

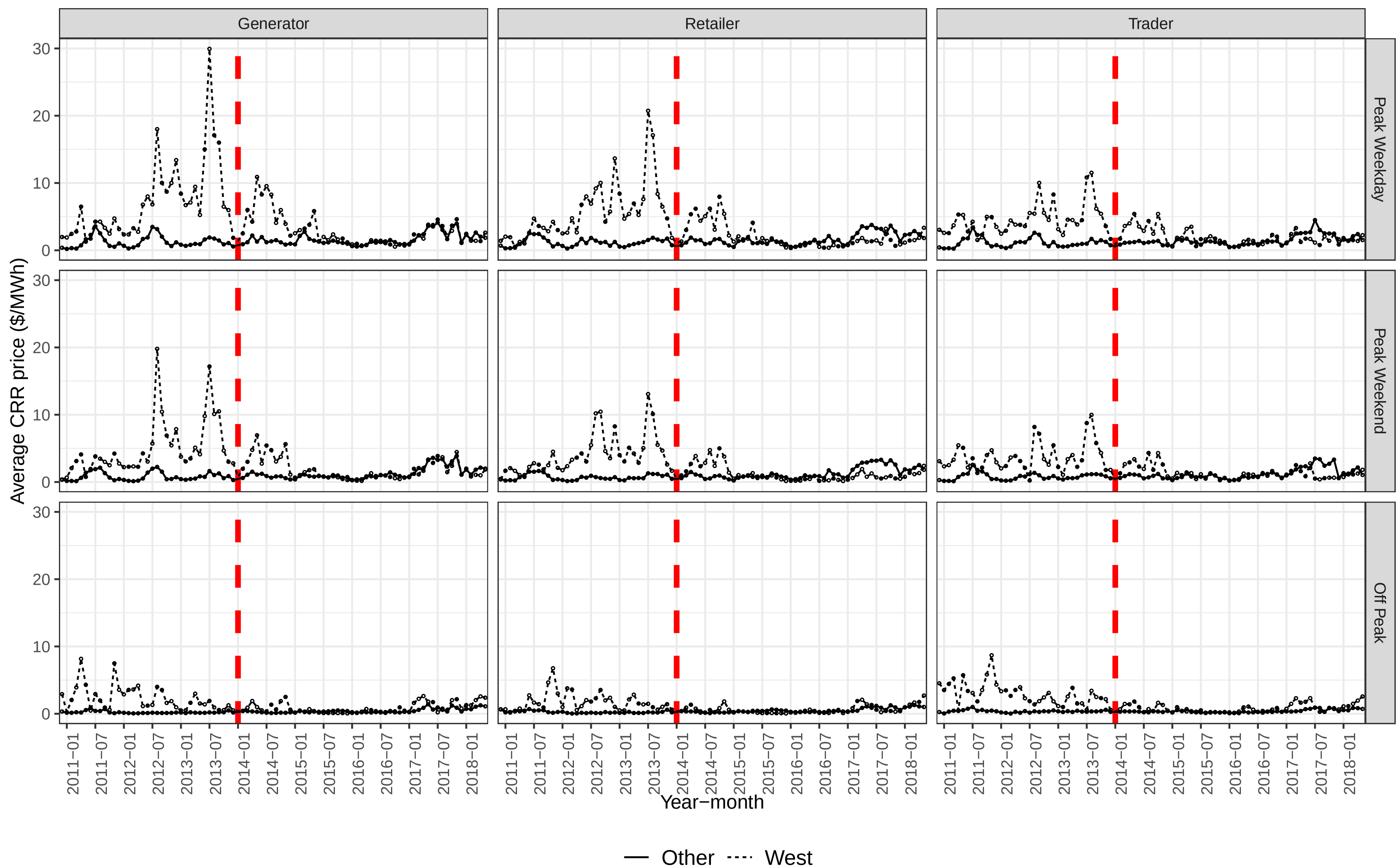


Figure A.3: Convergence of average market clearing prices($/MWh) between CRRs with West Source/Sink and Other Source and/or Sink post CREZ transmission integration. Dashed vertical line marks CREZ completion: January 2014.